Financial Shocks, Productivity, and Prices

Simone Lenzu* David A. Rivers† Joris Tielens‡

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Abstract

We study the interconnection between the productivity and pricing effects of financial shocks. Combining administrative records on firm-level output prices and quantities with quasi-experimental variation in credit supply, we show that a tightening of credit conditions has a persistent, yet delayed, negative effect on firms' long-run physical productivity growth (TFPQ) but also induces firms to change their pricing policies. As a result, commonly used revenue-based productivity measures (TFPR)—which conflate the pricing and productivity effects—offer biased predictions regarding the consequences of financial shocks for firms' productivity growth, underestimating the long-run elasticity of physical productivity to credit supply by almost half. Moreover, we show that the pricing adjustments themselves also have productivity implications. Firms coping with a contraction of credit use low pricing as a source of internal financing, allowing them to avoid cutting expenditures on productivity-enhancing activities, thereby softening the impact of financial shocks on long-run productivity growth.

Keywords: Productivity, Pricing, Financial Constraints, Innovation.

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*New York University, Stern School of Business, E-mail: slenzu@stern.nyu.edu; †University of Western Ontario, E-mail: drivers2@uwo.ca; ‡KU Leuven and National Bank of Belgium, E-mail: Joris.Tielens@nbb.be. We thank Tobias Berg, Andrea Caggese, Robert Engle, Marcela Eslava, Filippo Mezzanotti, Holger Mueller, Cecilia Parlatore, Gordon Philipps, Nicola Pierri, Alexi Savov, Johannes Stroebel, Olivier Wang, and participants and discussants at NYU Stern, Columbia Workshop in New Empirical Finance, RCEA Growth, Innovation and Entrepreneurship Conference, IMF, European Summer Meeting of the Econometric Society, Eastern Finance Association, FINEST workshop, EBRD Finance and Productivity conference, International Industrial Organization Conference, Midwest Finance Association, Barcelona GSB Summer Forum, North American Meeting of the Econometric Society, and European Association Industrial Organization meeting for the useful comments and suggestions. Lenzu thanks the Center for Global Economy and Business at NYU Stern, and Rivers thanks the Social Sciences and Humanities Research Council of Canada for their generous financial support. We thank Jun Wong and Cangyuang Li for excellent research assistance. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the National Bank of Belgium, the Eurosystem, or any other institution with which the authors are affiliated.

1 Introduction

Financial crises are frequently followed by persistent slowdowns in aggregate productivity growth (Cerra and Saxena, 2008; Reinhart and Rogoff, 2014; Hall, 2015). This has been recently documented for the U.S., Europe, and several developing countries in the wake of the Great Recession and subsequent sovereign debt crisis.[1] One explanation is that financial market conditions affect the ability of individual producers to sustain productivity growth (Midrigan and Xu, 2014; Cole, Greenwood, and Sanchez, 2016; Caggese, 2019).

Despite the growing interest in this topic, studying micro-level productivity slowdowns and their drivers remains challenging. A key difficulty lies in their measurement: commonly used revenue productivity measures conflate output prices with physical productivity. Accordingly, observed productivity slowdowns could indicate an actual decline in physical productivity growth, declining output prices, or both.

In this paper, we construct a novel dataset that allows us to directly address this empirical challenge and systematically examine the separate physical productivity and output price responses to a contraction in credit supply, as well as their relationship. Our analysis demonstrates that accounting for the endogenous response of prices is crucial for measuring and understanding how firms respond to financial shocks and the associated implications for productivity growth.

We find that a sudden tightening of financial conditions causes a delayed, but persistent and economically significant reduction in firm-level physical productivity growth (TFPQ). Revenue-based measures of productivity (TFPR), however, provide biased estimates of the effects on physical productivity as they also capture a change in pricing policies.[2] In the immediate aftermath of the credit crunch, firms cut output prices and, as a result, TFPR estimates suggest a short-run slowdown of firm-level productivity growth, despite TFPQ being unaffected. In the medium-to-long run, the TFPR and TFPQ responses are correlated, however the former substantially understates the decline in the latter because firms more affected by the shock eventually raise prices.

[1] See Jordà, Schularick, and Taylor (2013), Reifschneider, Wascher, and Wilcox (2015), and Queralto (2020).

[2] The TFPR-TFPQ terminology, now standard in the literature, was first introduced by the seminal contribution of Foster, Haltiwanger, and Syverson (2008). See Syverson (2011) for a discussion of the relationship between quantity- and revenue-based productivity measures.

Furthermore, we show that firms that are able to respond to the shock in the short run by lowering output prices experience a significantly lower contraction in productivity growth in the long run. The reason is that financial shocks deprive firms of the liquidity needed to fund investments in innovation and human capital that sustain productivity growth over time. By using low prices as a source of internal finance, firms can generate liquidity from the product market, allowing them to relieve the pressure to reduce expenditures in productivity-enhancing investments.

The findings in this paper offer a novel perspective and new insights regarding the contribution of financial factors to firm-level productivity growth. For one, they suggest that the consequences of financial shocks are sizable but take time to materialize, although movements in prices convey the (mistaken) impression that they impair firm-level productivity immediately. For another, they reveal that the price adjustments themselves have direct implications for productivity growth, as firms can use pricing adjustments as a source of internal finance.

To perform our analysis, we build a novel micro-level panel dataset that spans a decade of business and credit records for manufacturing firms in Belgium. Combining confidential administrative data from different sources, our dataset merges information on firms' product-level output prices and quantities, a detailed account of firms' balance sheets and income statements, and comprehensive records of firm-bank credit relationships. The availability and granularity of firm/product-specific prices enable us to build firm-level price indices that aggregate across the heterogeneous products of multi-product firms and allow us to compute firm-level technical efficiency measures.

The national business credit registry offers a detailed account of firms' overall access to bank finance, as well as disaggregated information on their credit suppliers and their individual positions with firms. By combining this information with the occurrence of an aggregate financial shock that differentially affected lending institutions in Belgium, we are able to isolate variation in firm-level credit driven by changes in credit supply, separately from changes in credit demand. Specifically, we use the burst of the 2010-2012 European sovereign debt crisis as a natural experiment to construct a set of firm-specific credit supply shifters. The variation in these shifters is driven by heterogeneity in the holdings of distressed sovereign securities in banks' balance sheets. We show that the balance sheet shock suffered by banks was passed through to producers in the form of a credit tightening (both lower quantity and higher financing costs). This variation allows us to identify the causal impact of credit supply shocks on firm-level productivity growth and pricing behavior.

Our estimates reveal that firms coping with a tightening of credit supply experience a significant contraction in TFPQ growth that materializes three years after the credit shock and persists over time. Specifically, we estimate that a one standard deviation difference in exposure to the credit shock translates into a reduction of long-run productivity growth by 8.5 percent, which implies a long-run elasticity of firm-level productivity to credit supply of 0.7. The persistent productivity slowdown helps rationalize the slow economic recovery after financial crises documented by previous studies (Queralto, 2020).

A rather different picture emerges when we examine estimates based on TFPR. The reason is that revenue-based productivity estimates capture not only changes in physical productivity, but also changes in firm output prices, which we show are also directly affected by the shock. In the short-run, the shock induces firms to reduce prices, with a one standard deviation difference in exposure to the shock leading to a 2 percent drop in prices, whereas TFPQ is unaffected. As a result, the TFPR estimates erroneously suggest that firms facing a financial shock experience an immediate slowdown of productivity growth. In the long-run, firms eventually increase prices in response to the shock, with a one standard deviation in exposure generating a 4 percent increase in prices by the end of our sample period (seven years after the shock). Consequently, while revenue and physical productivity growth do co-vary over longer horizons, TFPR estimates significantly understate (by about half) the true impact of a tightening of financial conditions on physical productivity growth.

After decoupling the productivity and price effects of financial shocks, we provide evidence on the economic mechanisms underlying these responses. First, we show that the sudden tightening of credit supply conditions has an immediate, contractionary effect on expenditures on productivity-enhancing activities, such as investments in innovation and worker's human capital. Using variation in these expenditures driven by firms' heterogeneous exposure to the credit shock, we then show that the contraction in investments in intangibles leads to a persistent, yet delayed, reduction in firm-level productivity growth. Specifically, we estimate that a one percentage point reduction in the probability of undertaking any R&D investment translates into a decrease in long-run productivity growth of almost 2 percent. Similarly, a one percent reduction in R&D and training expenses leads to decreases of productivity of over 3 percent and 0.8 percent, respectively.

Next, we study the mechanisms underlying the price response. First, we document that the credit supply shock led firms to seek alternative, more expensive, sources of external funding, leading to an increase in borrowing costs. Second, as discussed above, the shock reduced long-run productivity growth for firms. Together, higher financing costs and lower production efficiency lead to an increase in operating costs, which explains why prices of producers more exposed to the credit crunch increase in the long-run, compared to less exposed producers.

A fundamentally different force explains the contraction of output prices in the immediate aftermath of the shock. The sudden tightening of credit supply conditions starves firms of liquidity and exposes them to the risk of financial distress. Since cutting costs or raising external finance from alternative sources takes time or might not be possible, firms use low pricing as a source of internal finance to counteract the reduction in external finance (Hendel 1996). A more aggressive pricing strategy, while sub-optimal in normal circumstances, allows firms to generate additional cash flows by selling off their inventories (Kim, 2020).

By decoupling the effects of financial shocks on firm productivity and pricing, our results not only enhance our understanding of the real and nominal effects of financial shocks, but also reveal an important inter-temporal relationship between them. We show that a strong, negative correlation exists between a firm's short-term price response and long-run productivity growth. That is, firms that price more aggressively in reaction to the financial shock are the ones that experience a less pronounced long-run contraction in productivity growth. The explanation we propose is that liquidity is fungible, and firms that can leverage price reductions as a source of internal finance are able to avoid significant reductions in productivity-enhancing investments, thus softening the long-run impact on productivity.

To provide evidence for this hypothesis, we leverage cross-sectional variation in characteristics that capture heterogeneity in a firm's latent ability to respond to the credit tightening by lowering prices. Previous work has shown that liquidity constrained firms shed inventories when hit by financial shocks (Gertler and Gilchrist, 1994; Kashyap, Lamont, and Stein, 1994) and that firms with larger inventory holdings are more likely to drop prices in the attempt to generate extra cash flows from the product market (Kim, 2020).[3] Based on these insights—which also find support in our data—our first measure exploits within-industry heterogeneity in the (pre-shock) availability of firm-level inventories of finished products. Our second measure exploits cross-industry heterogeneity in the price elasticity of consumer demand. This is based on the idea that producers facing more elastic demand can more easily expand sales, and thus liquidity, by lowering output prices.

We first show that both measures are highly predictive of the observed price response. We then document that producers that can more readily adjust their pricing policies reduce their expenditures on productivity-enhancing activities less than other producers, and as a result they experience lower reductions in productivity growth in the long run. To interpret the economic importance of this channel, we compare the long-run productivity effects of producers similarly exposed to the credit supply shock, but that differ in their ability to reduce prices in the short-run (25th versus 75th percentile of both measures). We find that producers that are better able to respond to the shock by pricing more aggressively experience a contraction in long-run TFP growth that is 25 percent smaller.

Relation to the literature. This paper contributes to the literature studying the relationship between finance and productivity growth, and more specifically the influence of financial market conditions on producers' technical efficiency.[4] Using aggregate data from advanced economies and emerging market economies, Queralto (2020) documents a persistent productivity drop following financial crises, suggesting that financial tightening acts as a drag on business productivity. Midrigan and Xu (2014) develop and calibrate a quantitative model highlighting the role played by financial frictions in determining firm-level TFP growth. More closely related to our study, Caggese (2019) and Manaresi and Pierri (2018) offer micro evidence on the negative relationship between financial frictions and firm-level revenue productivity growth.[5] To the best of our knowledge, our paper is the first to quantify the causal effects of financial shocks on

[3]See also Hendel (1996) for a theoretical treatment.
[4]See Levine (2005) for a review of the finance and growth literature.
[5]See also Levine and Warusawitharana (2021) and Duval, Hong, and Timmer (2020).

firm-level productivity, disentangling changes in technical efficiency from simultaneous pricing effects.

Our paper also relates to a strand of studies documenting that revenue and physical productivity estimates may offer intrinsically different predictions in a variety of contexts. Foster, Haltiwanger, and Syverson (2008) explores the separate influence of physical productivity and demand on firm survival. Others emphasize the distinction between revenue and physical productivity when studying the implications of resource misallocation (Hsieh and Klenow, 2009; Haltiwanger, Kulick, and Syverson, 2018), foreign market participation (Katayama, Lu, and Tybout, 2009), trade liberalization (Eslava et al., 2013), learning-by-exporting (Garcia-Marin and Voigtländer, 2019), and firm dynamics (Eslava and Haltiwanger, 2020). We are the first to show that distinguishing between the two productivity measures is crucial to understanding the implications of financial shocks on firm productivity. Moreover, the bifurcation between the short-run TFPR and TFPQ effects is the result of a novel mechanism that is not ascribable to the demand– and supply–side explanations documented thus far in the literature. In contrast, it is driven by firms' responses to a sudden tightening of credit market conditions, which leads them to fundamentally change their behavior in the product market.

Finally, our paper bridges the finance-and-productivity literature with the previously unconnected literature studying how financial factors influence producers' pricing policies.[6] Within this literature, our paper is closest to Kim (2020), which documents a reduction of firms' output prices in response to a credit supply shock, emphasizing the role played by inventory management. By studying both prices and productivity together, our paper demonstrates that the use of low pricing as a way to raise liquidity from the product market has not only nominal implications (pricing behavior), but also important real effects, as it mediates the impact of financial shocks on long-run productivity growth.

The paper proceeds as follows. Section 2 describes the datasets we use to conduct our empirical analysis and discusses issues related to the measurement of prices and productivity. Section 3 details the empirical design that allows us to identify firm-level

[6] Chevalier (1995a) and Chevalier and Scharfstein (1995; 1996) provide empirical evidence that a firm's financial condition affects its pricing strategy. Borenstein and Rose (1995), Busse (2002), and Phillips and Sertsios (2013) document a contraction of firm output prices in response to financial shocks. Gilchrist et al. (2017) studies the role played by firms' liquidity constraints in the determination of inflation dynamics during the Great Recession.

credit supply shocks. Section 4 presents our main results on the separate effects of credit supply shocks on productivity and prices. Section 5 studies the economic forces underlying these effects. Section 6 explores the dynamic link between the price and productivity effects. Section 7 concludes.

2 Data and measurement

The central objective of our analysis is to understand the consequences of financial shocks on productivity and pricing dynamics, as well as their relationship. To this end, we construct a novel product-firm-bank-matched dataset that allows us to observe information on product-level prices and quantities of the individual goods produced by manufacturing firms in Belgium, as well as detailed accounts of their production choices, assets and liabilities structure, and access to credit markets. The granularity of these data allows us to overcome several data limitations of previous empirical studies interested in the finance-productivity nexus.

First, the availability of firm/product-specific prices enables us to disentangle price differences from differences in technical efficiency. In turn, this allows us to investigate how financing constraints separately affect prices and productivity and to study whether the two responses are related. Second, the credit registry records allow us to link individual producers with their lenders. Combined with detailed information about lenders' balance sheets, this allows us to exploit quasi-experimental variation in credit availability to quantify the causal relationship between financing shocks and the firm outcomes of interest. Third, our data comprises a rich set of firm-balance sheet variables that allows us to explore why firm productivity is affected by the availability of credit and how this relationship is related to and affected by firms' pricing response.

In what follows, we elaborate on the relevant aspects of our data and discuss how we exploit it to construct firm-level price indices and estimate firm-level physical productivity measures. Additional details on the sources and definitions of the variables are provided in Appendix A.

2.1 Data

Our dataset combines confidential information from four administrative datasets covering manufacturing firms in Belgium: the PRODCOM survey; firms' annual accounts; corporate credit register records; and individual bank balance sheets.

Product-level prices and quantities. We use the PRODCOM database to obtain detailed information on firms' real activity (value and quantity of production) for all manufacturing products for a large sample of firms. The PRODCOM survey, commissioned by Eurostat and administered in Belgium by the National Statistical Agency, is designed to cover at least 90% of production value within each NACE 4-digit manufacturing industry by surveying all firms operating in the country with (a) a minimum of 20 employees or (b) total revenue above 4.5 million euros (European Commission, 2014).[7] The surveyed firms are required to disclose product-specific revenues (in euros) and quantities (e.g., volume, kg., m^2, etc.) of all products sold on a monthly basis, disaggregated at the 8-digit product level (e.g., 15.93.11.93 for "Sparkling wine, alcohol by volume > 8.5%", 15.93.11.95 for "Sparkling wine, alcohol by volume ≤ 8.5%"). These data allow us to compute product- and firm-level prices. They also enable the construction of appropriate quantity-based measures of output for use in the production function estimation.

Firm balance sheets and real investment activity. Data from the firms' annual accounts (AA) from the Belgian central balance sheet office provide us with detailed information on total firm revenues, production inputs (capital, labor, intermediate inputs), and the stock of inventories. These variables, combined with the price and quantity data from PRODCOM, allow us to estimate quantity-based production functions and recover firm-level technical efficiency. Moreover, the AA also contain information on firms' investments in R&D and employee training—commonly regarded as productivity-enhancing expenses—that allow us to shed light on the channels through which credit tightening affects productivity responses and how the ability to adjust prices can mediate these effects.

[7] The statistical classification of economic activities in the European Community, commonly referred to as NACE, is the standard industry classification system used in the European Union.

Credit data. A key feature of our data, used in the construction of the firm-specific credit supply shifters, is the ability to measure the amount of bank credit received by each firm from individual lenders. Unique firm identifiers allow us to merge our firm-product-level data with confidential firm-bank records from the Belgian Corporate Credit Registry (CCR). This data provides us with information on firms' credit relationships and monthly credit balances maintained with each financial institution operating under the supervision of the National Bank of Belgium (NBB).[8]

Bank balance sheets. As we explain in more detail in Section 3, the linchpin of our identification strategy is the burst of the European sovereign debt crisis—and subsequent contraction of bank credit—that followed the bailout of the Greek sovereign debt in 2010. We leverage information on firms' heterogeneous exposure to banks differentially impacted by the European sovereign crisis in order to isolate firm-specific variation in credit availability (i.e., movements in credit supply). To do so, we merge in bank balance sheet data from the NBB supervisory records, which provide us with quarterly accounting information on the balance sheets and income statements for each bank in the CCR. The key variable of interest is the bank-level stock of sovereign securities that experienced a significant loss in value after the burst of the European sovereign crisis.

Sample properties. Our final sample consists of 1,024 firms and a total of 9,667 firm-year observations between 2006 and 2016. To construct this sample, we start with the PRODCOM database, focusing on firms whose main activity is within manufacturing, and merge in the data from the AA and the CCR, dropping observations with missing information on prices and on variables used in the productivity estimation (inputs and outputs).[9] We focus our analysis on an 11-year window centered around the Greek sovereign bailout (2006-2016), restricting our sample to firms with active lending relationships in the twelve months before the Greek bailout.[10] This allows us to evaluate trends in the data prior to the bailout event as well as examine subsequent outcomes at

[8]To harmonize the frequency of the CCR records with that of the AA variables, we sum each firm's monthly credit balances across its lenders and compute firm-level yearly debt balances averaging across months of each fiscal year.

[9]In order to perform the production function estimation, we focus on industries (NACE Rev. 1.1 2-digit codes) with at least 50 firms and 200 firm-year observations. This leaves us with 16 industries, which covers over ninety percent of total manufacturing output in PRODCOM.

[10]We require firms to have a positive credit balance in the pre-period in order to study how firms' credit market access changed following the sovereign crisis.

both short and long horizons. To minimize the impact of outliers, we trim the observations at the tails of the firm-level price growth distribution (top and bottom one percent) and winsorize variables measured in levels (growth rates) at the one percent (2.5 percent) level. Table 1 presents the summary statistics of the key variables used in the empirical analysis.

2.2 Measurement of prices and productivity

Price measurement. Our analysis requires a firm-level price index that aggregates across the heterogeneous products of multi-product firms. To do so, we follow the consumer preference-based price index (CUPI) approach introduced by Redding and Weinstein (2020), which accounts for changes in the composition and quality of products within a firm. In Appendix F, we show that our results are robust to several alternative ways of constructing a firm-level price index, including a revenue-share weighted price index and the price of the firm's main product.

The exact definition and properties of the price index are presented in Appendix B. Here we briefly describe the key features. We build the price index for firm j in year t, denoted P_{jt}, by recursively concatenating year-to-year changes in the CUPI, starting from a firm-specific base year:

$$P_{jt} = P_{jB} \prod_{\tau=B+1}^{t} \tilde{P}_{j\tau}. \tag{1}$$

Yearly changes in the firm-level price index, $\tilde{P}_{j\tau}$, are driven by changes in the prices and shares of continuing products, the entry and exit of products in the firm's portfolio, and changes in the quality/appeal of existing products.[11] Following Eslava and Haltiwanger (2020), we construct the base price index, P_{jB}, as a geometric average of the prices of all products of firm j in the base year B scaled by the average price for that product. This allows us to capture cross-sectional differences in prices across firms, which are important for the purposes of the productivity estimation.

[11] To ensure comparability of product-level prices across firms and within firms over time, we define products as unique combinations of 8-digit PRODCOM product codes and units of quantity measurement (e.g., liters, kilograms, etc.). We then compute unit values for each product (i.e., prices) by dividing total value by total quantity for each firm-product-time observation.

Productivity estimation. We estimate firm-level physical productivity (TFPQ) as the residual from a gross output production function:

$$\ln TFPQ_{jt} = q_{jt} - f(k_{jt}, l_{jt}, m_{jt}; \gamma), \tag{2}$$

where lowercase letters denote logs. The variable q_{jt} denotes firm-level output (quantity) produced by firm j in year t. The variables k_{jt}, l_{jt}, m_{jt} denote capital, labor, and intermediate inputs, respectively. $f(\cdot)$ is the (log) production function, and γ is a vector of structural parameters to be estimated. TFPQ captures a firm's capability to turn inputs into physical output. As explained in Foster, Haltiwanger, and Syverson (2008), it is the appropriate measure of a firm's technical efficiency, essentially reflecting its average per unit cost of production. Particularly relevant for our purposes is the within-firm variation of this measure, which is influenced by the evolution of the firm's technological fundamentals and production line practices that can be affected by a tightening of external finance conditions.

We use the price index in equation (1) to construct a firm-level quantity index, Q_{jt}, by dividing firm-level revenues by the firm-level price index.[12] On the input side, we measure labor services using the deflated wage bill and construct a measure of capital stock from investments in fixed assets following the perpetual inventory method. Intermediate inputs are measured as the total value of materials and services used in production. We deflate labor, capital, and intermediate inputs by the corresponding industry-year price deflators. We model the production function $f(\cdot)$ non-parametrically, without imposing any restrictions on the elasticity of substitution between different inputs. This allows us to estimate *firm-time-specific* output elasticities that depend on the industry-specific technology and the firm-specific input mix: $\theta^x_{jt} = \theta^x(k_{jt}, l_{jt}, m_{jt}; \gamma), \quad x = \{K, L, M\}$.

We estimate the production function separately for each industry, based on the approach developed in Gandhi, Navarro, and Rivers (2020), and augmented to control for differences in output quality (De Loecker et al., 2016).[13] This structural approach identifies the production function by addressing the simultaneity bias that derives from the correlation between input choices and unobserved (to the econometrician) productivity

[12] In order to adjust our output measures for changes in inventories, we first adjust revenues by the change in the value of inventories, and then apply the firm-level price index to compute the adjusted quantities.

[13] The details of the estimation routine are provided in Appendix C.

(Marschak and Andrews Jr., 1944), and it solves the identification problem that affects the estimates of the output elasticities of flexible inputs.

As with other recent structural methods for estimating productivity, Gandhi, Navarro, and Rivers (2020) assumes that productivity evolves according to an exogenous Markov process. We extend this approach by allowing productivity to evolve according to a controlled Markov process in which firm investments in innovation (R&D and employee training) affect future productivity growth.[14] As a robustness check, we also recover productivity using standard index-function methods, which do not rely on assumptions regarding the evolution of productivity. These results are similar to our main results, and are presented in Appendix F.

Finally, the approach of Gandhi, Navarro, and Rivers (2020) is based on a transformation of the firm's first-order condition for intermediate inputs. Since the European sovereign debt crisis (and preceding global financial crisis) may have generated frictions that caused firms to deviate from the unconstrained optimization, we perform the production function estimation using only data prior to 2008, and then apply the production function estimates to all years in order to compute productivity for the full sample.[15] The elasticity estimates are presented in Table A.2 in the Appendix.

To underscore the importance of decoupling the effects of financial shocks on firms' productivity growth and pricing policies, we compute two revenue productivity measures (TFPR). The first measure, which we denote as $\mathrm{TFPR}^{\mathrm{Q}}$, is based on the TFPQ estimates:

$$\ln TFPR_{jt}^{Q} = \ln TFPQ_{jt} + \ln P_{jt}. \tag{3}$$

This measure of TFPR has the advantage of preserving the identity that revenue productivity is the product of physical productivity and prices, thus making the decomposition of the effects of financial shocks on the two components of revenue productivity (prices and physical productivity) transparent and exact. The second revenue productivity measure, which we denote $\mathrm{TFPR}^{\mathrm{R}}$, is the common productivity measure adopted by previous studies exploring the finance productivity nexus in the absence of separate firm-level information on prices and quantities. It is constructed as the residual

[14] As in Ericson and Pakes (1995) and Doraszelski and Jaumandreu (2013), the distribution of firm productivity in period t depends on past expenditures on innovation as well as past realizations of productivity.

[15] We have also computed estimates of the production function using the full sample, and we find that they yield quantitatively very similar results.

from a production function estimation using firms' total revenues net of changes in inventories (deflated by an industry-level price index), r_{jt}, as a proxy of physical output:

$$\ln TFPR^R_{jt} = r_{jt} - f(k_{jt}, l_{jt}, m_{jt}; \tilde{\gamma}), \tag{4}$$

where we denote the vector of parameters that determine revenue elasticities by $\tilde{\gamma}$ to distinguish it from the vector of structural parameters that characterize the quantity production function in equation (2).[16]

3 Identification strategy

The firms' credit balances observed in the CCR data result from a combination of factors. Some are ascribable to the supply of credit, and others to firms' financial needs and investment opportunities, and therefore credit demand. Because the same events that change supply-side conditions may also trigger demand-side adjustments, we face a classic identification challenge in estimating how firm-level outcomes are affected by the availability of credit. We overcome this challenge by exploiting quasi-experimental variation in the credit supply faced by individual producers. This variation is driven by their heterogeneous exposure to lenders holding different amounts of distressed sovereign securities in the wake of the 2010-2012 European sovereign debt crisis.

Construction of credit supply shifters. The key event in our study is the bailout request advanced by the Greek government in April 2010, which sparked tension in European sovereign markets and led to a reassessment of the risk profile of sovereign securities issued by peripheral European counties (Greece, Italy, Portugal, Spain, and Ireland; GIPSI henceforth).[17] As shown in Figure 1, the events in Greece triggered a sharp increase in the spread between the yield to maturity of GIPSI's bonds and German bonds, which were regarded as safe assets. The sudden change in the risk profile of these securities had a poisoning effect on the balance sheets of financial intermediaries holding them, which, in turn, passed through the balance sheet shock to their borrowers in the form of a credit tightening. This can be seen in the aggregate raw data, which reveals a divergence in credit supply after the Greek bailout between banks with high versus low

[16] As pointed out by Klette and Griliches (1996), under general conditions, revenue elasticities might be biased and therefore be different from the elasticities estimated from quantity production functions.

[17] See Appendix E and Lane (2012) for a description of the European sovereign crisis.

exposure to distressed sovereigns (Figure A.2, Appendix E).

Belgian firms rely heavily on bank debt as a primary source of external finance. In our sample, only 1.35 percent of the firms are publicly listed; only 0.87 percent of them issue publicly traded bonds; the share of bank debt provided by banks reporting in the credit registry amounts, on average, to 21 percent of firms' total assets; and debt vis-à-vis financial institutions represents, on average, 80 percent of firms' long-term liabilities. Moreover, previous literature has shown that financial frictions prevent or limit a firm's ability to substitute toward alternative forms of external finance (Khwaja and Mian, 2008; Chodorow-Reich, 2014). Taken together, these observations suggest that a tightening of credit supply by a firm's legacy lender is expected to have important effects on firm's real activity.

Following Bottero, Lenzu, and Mezzanotti (2020), we use the Greek bailout as a natural experiment to construct a set of firm-specific credit supply shifters based on the presence and importance of firms' credit relationships with lenders differentially exposed to distressed sovereign securities. In particular, we construct them by measuring the (weighted-average) exposure of firm j's lenders to the sovereign shock:

$$\text{Shock}_j = \sum_{b \in \mathcal{B}_j} \omega_{jb} \cdot \text{GIPSI Sovereigns}_b,$$

where $\mathcal{B}_j$ is the set of financial institutions lending to firm j in 2010:Q1, the quarter prior to the Greek bailout request, ω_{jb} is the share of firm j's credit received from bank b in the same quarter, and the variable "GIPSI Sovereigns$_b$" measures bank b's holdings of sovereign securities issued by GIPSI countries in 2010:Q1, scaled by bank b's risk-weighted assets. By focusing on pre-bailout holdings we ensure that our measure is not affected by any endogenous portfolio adjustment that banks made in response to the sovereign crisis itself (Becker and Ivashina, 2018).

At the onset of the sovereign crisis, the average firm in our sample was borrowing from a pool of banks that invested a substantial fraction of their assets (14 percent) in sovereign bonds issued by peripheral European countries. We also observe significant dispersion in firm exposure, as indicated by the standard deviation of Shock$_j$ (4.6 percent). To facilitate the interpretation of the treatment effects, we de-mean and scale Shock$_j$ by its standard deviation.

Econometric specification. Leveraging the heterogeneous exposure of individual firms to the sovereign crisis, we estimate empirical impulse-response functions of productivity and prices to the credit supply shock via local linear projections (Jordà, 2005). Specifically, we run a sequence of cross-sectional regressions over different time horizons, indexed by τ:

$$\Delta_\tau Y_j = \beta_\tau \cdot \text{Shock}_j + \Gamma^{'}_{K,\tau}\mathbf{K}_j + \Gamma^{'}_{X,\tau}\mathbf{X}_j + i_{ind,\tau} + i_{reg,\tau} + u_{j\tau}. \tag{5}$$

The left-hand-side variable $\Delta_\tau Y_j$ measures the *cumulative* growth rate of a firm-level outcome variable between the year prior to the burst of the crisis, 2009, and year $2009+\tau$, $\tau = \{1, ..., 7\}$. $\mathbf{X}_j$ is a set of firm-level controls; $\mathbf{K}_j$ is a set of bank-level controls; and i_{ind} and i_{reg} are industry and region fixed effects. The coefficients of interest, β_τ, measure the cumulative effect of a credit supply shock on firm outcomes over different horizons.

We follow Acharya et al. (2018) and Bottero, Lenzu, and Mezzanotti (2020) by including bank-level controls ($\mathbf{K}_j$), all of which are measured before the Greek bailout in order to account for the fact that a bank's level of sovereign holdings is correlated with other bank characteristics (e.g., capitalization and exposure to stability of funding) that might affect a bank's propensity to adjust credit supply following the burst of the sovereign crisis.[18]

Previous work has shown that the pass-through of bank balance sheet shocks to borrowing firms depends on the strength of firm-bank ties (Petersen and Rajan, 1994). Moreover, the contraction of credit supply by one lender can, in principle, be smoothed by an increase of credit supply by others. Therefore, in all our regression models we account for firms' heterogeneous scope and strength of credit market interactions by controlling for the average length and number of lending relationships of the borrower ($\mathbf{X}_j$), measured before the burst the of the crisis.

By restricting the analysis to within industry and region variation through the inclusion of detailed fixed effects, we address the possibility that lenders with high sovereign holdings might specialize in industries or geographical regions experiencing a more severe contraction of economic activity (Paravisini et al., 2014).[19] In particular,

[18]The bank-level controls in $\mathbf{K}_j$ include measures of lenders' size, funding structure, liquidity position, and quality of the lending portfolio. Similar to our measure of GIPSI sovereign exposure, each of these variables is constructed as a firm-level weighted average of the lender-specific variables, measured in the last quarter before the shock (2010:Q1), using as weights the share of firm j's credit received from each bank (ω_{jb}). See Appendix A for further details on the sources and definitions of the control variables.

[19]Region fixed effects flag in which of the three Belgian regions (the Flemish region, the Walloon region,

this granular set of fixed effects ensures that the estimated productivity and price effects are not picking up firms' responses to a contraction of local, industry-level, or aggregate demand that might have taken place as a consequence of the tensions in sovereign markets (Bocola, 2016).

A few further estimation details bear noting. First, by estimating the model in first-differences we control for any unobserved, time-invariant characteristics which might vary between more and less exposed firms. Second, because we normalize Shock_j to have mean zero and unit standard deviation, the coefficients β_τ measure the effect of a one standard deviation difference in the exposure to the credit shock on the $\tau-$year cumulative growth rate of variable Y_j. Third, all reported standard errors are clustered at the main lender-level to account for the correlation of residuals across producers that share the same main lender and therefore are exposed to a similar treatment effect (Khwaja and Mian, 2008).

Exposure to the sovereign debt crisis and credit availability. We begin by showing that the burst of the sovereign crisis impaired access to credit for firms borrowing from lenders highly exposed to distressed sovereigns.[20] Figure 2, panel a, presents the dynamic effect of exposure to the sovereign shock on firms' cumulative bank credit growth ($\Delta_\tau \text{Credit}_j$), estimated according to model (5).[21] (The full regression output is reported in Appendix E.) A one standard deviation increase in lenders' exposure to GIPSI sovereigns corresponds to a (cumulative) reduction of about 17 percent of firms' total bank credit in the three years following the burst of the sovereign crisis.

The sovereign shock not only affected firm access to external finance but also its cost. While we do not have direct information on bank-specific lending rates, we can construct a proxy of firms' average financing costs using the ratio of financial charges over financial debt from the AA data ($\Delta_\tau fc_j$), and study how this measure of financing costs changes in the aftermath of the Greek bailout as a function of the firm's exposure to

and the Brussels-Capital region) the firm is headquartered. Industry fixed effects are measured using the industry code of the main product of the firm (measured in terms of production value in PRODCOM).

[20]Our estimates are in line with those in Bottero, Lenzu, and Mezzanotti (2020) and Acharya et al. (2018). They document a contraction of credit supply by Italian banks and by banks operating in the European syndicated loan market, respectively.

[21]As in Chodorow-Reich (2014), we measure the cumulative growth in total bank credit of each firm as $\Delta_\tau \text{Credit}_j = \frac{\text{Credit}_{j,2009+\tau} - \text{Credit}_{j,2009}}{0.5(\text{Credit}_{j,2009+\tau} + \text{Credit}_{j,2009})}$, where $\text{Credit}_{j,2009}$ measures the average outstanding bank credit of firm j in the year prior to the shock, and $\text{Credit}_{j,2009+\tau}$ measures the average outstanding credit τ-years afterwards.

banks with differential holdings of distressed sovereigns.[22] Figure 2, panel b, shows that a one standard deviation increase in lenders' exposure to GIPSI sovereigns eventually leads to an increase in the the average cost of finance by about 3 percent in the years that followed the burst of European sovereign crisis. Taken together, the movement of the quantity and cost of finance in *opposite* directions is consistent with a tightening of credit supply conditions, as a contraction in credit demand would have led to a reduction of both quantity and prices.

To provide further evidence that our results are driven by a sudden tightening of credit supply, rather than by demand-side factors, we leverage the availability of micro-data on individual firm-bank relationships and estimate a version of model (5) at the firm-bank relationship level, augmenting the regression model with firm-level fixed effects. This within-firm specification allows us to test whether banks with higher GIPSI holdings reduced their credit supply to the *same firm* relative to banks with lower GIPSI holdings, thereby controlling for unobservable changes in firm-specific factors, such as a contraction in credit demand or a worsening of firms' credit worthiness. The results, reported in Appendix E, indicate that indeed more exposed banks reduced lending relative to less exposed banks lending to the same firm. In addition, while the within-firm estimates are largely unaffected by whether we include firm-fixed effects, the R^2 of the regressions increase by a factor of seven to thirteen, depending on the time horizon, after inclusion of the fixed effects. In the spirit of Oster (2019), this observation demonstrates that while unobserved firm-specific factors (e.g., changes in credit demand) are important for explaining the overall variation in bank lending to firms, that variation is not correlated with exposure to the sovereign shock.

Finally, in order to interpret this credit contraction as capturing the causal effects of shocks to credit supply, it has to be the case that, absent the sovereign debt crisis, firms borrowing from banks with high GIPSI exposure would not have experienced a differential change in their credit supply relative to firms borrowing from banks with low exposure. Two pieces of evidence lend support to this parallel trends assumption. First, Table A.1 in Appendix A shows that the sample of firms borrowing from more and less exposed lenders appears well-balanced on observable pre-shock characteristics, including size,

[22] We measure average financing costs as $fc_{j,t} = \frac{\text{Financial Charges}_{j,t}}{\text{End of Year Financial Debt}_{j,t-1}}$. We then compute the firm-level change in this variable relative to 2009 ($\Delta_\tau fc_j = fc_{j,2009+\tau} - fc_{j,2009}$) over different horizons $\tau = 1, ..., 7$.

bank leverage, productivity, and price level. Second, in direct support of the assumption, Figure 2 shows no differential trends in credit market outcomes between more and less affected firms prior to the sovereign shock.

4 Decoupling the effect of financial shocks on productivity and prices

Having established the pass-through of lenders' balance sheet shocks to firms' credit supply, we now turn to quantifying the separate effects of the credit tightening on firm-level productivity and prices. In Table 2, we present the estimated cumulative responses according to model (5). Figure 3 provides a visual representation of these results.

Productivity response to financial shocks. We begin by studying the response of TFPR, which is the commonly used proxy for physical productivity when information on firm-level prices is unavailable. Columns 1 and 2 present the estimated response of TFPR growth using the two revenue productivity measures described in Section 2. In line with previous findings (see, e.g., Manaresi and Pierri, 2018), we find that exposure to the credit supply shock leads to a statistically and economically significant contraction of revenue productivity growth that materializes in the immediate aftermath of the shock and persists over time. We estimate that an increase of a firm's exposure equal to one standard deviation of our shock variable leads to a contraction of 1.5−1.8 percent of its revenue productivity growth one year after the shock (short-run effect) and of 4.3−4.9 percent after seven years (long-run effect), depending on the measure.

The estimated TFPQ response, however, paints a substantially different picture regarding the timing and magnitude of the implications of a credit tightening on firms' productivity growth (column 3). First, in stark contrast with the TFPR estimates, credit supply shocks have *no impact* on firms' physical productivity (TFPQ) growth in the short run. The estimated effect becomes economically sizable and statistically significant only three years after the shock. Second, revenue-based measures also offer a biased prediction regarding the long-run effects of the shock on physical productivity growth. While TFPR and TFPQ move in the same direction over the medium-long run, the estimated contraction in productivity growth is about twice as large than the one suggested by the revenue-based estimates. Figure 4 helps visualize this finding, overlapping the estimates in columns 1, 2, and 3. A one standard deviation exposure to the shock translates into a contraction of 8.5 percent in firms' physical productivity growth by the end of our sample period. Combined with the effects of the shock on firm-level credit growth, these estimates imply a long-run elasticity of firm-level physical productivity to credit supply of about 0.7, which is considerably larger than the elasticity implied by the revenue-based estimates (0.36–0.41).

Price response to financial shocks. The empirical evidence presented above reveals that, in the short-run, estimates based on TFPR are substantially *upward biased*, whereas over longer horizons, they are substantially *downward biased*. We now show that the bifurcation between the revenue-based and quantity-based productivity growth effects is driven by a statistically significant and economically meaningful adjustment of firms' output prices in response to the tightening of financial conditions. In fact, in the case of the TFPR^{Q} measure, the difference between the effect on TFPR and TPFQ is exactly equal to the price effect, by construction.

The estimates in column 4 of Table 2 indicate that producers coping with an unexpected contraction in credit supply immediately adjust output prices downward. A one standard deviation increase in exposure to the credit shock implies, on average, an immediate reduction of about 2 percent in firms' output prices, which is responsible for driving the entire contraction in revenue productivity observed in the data. The short-term reduction of output prices is consistent with empirical findings in previous works documenting how firms adjust their short-term pricing policies in response to a deterioration of financing conditions (Borenstein and Rose, 1995; Busse, 2002; Phillips and Sertsios, 2013; Kim, 2020).

However, the price contraction is short-lived. As shown in Figure 3 and Table 2, firms that were more exposed to the credit shock eventually increase their prices relative to less exposed firms. A one standard deviation increase in exposure to the credit shock implies an increase of about 4 percent in firms' output prices by the end of our sample period. Importantly, while short-run adjustments in revenue-based productivity solely pick up the movements in output prices, in the same way, the subsequent rebound of output prices explains why inference based on revenue-based measures substantially underestimates the long-run slowdown of physical productivity growth.

Robustness analysis. We conduct a series of robustness checks to demonstrate the robustness of the estimated productivity and pricing effects. The results are presented in Appendix F.

We first show that the estimated effects of financial shocks on productivity growth are robust to alternative ways of measuring productivity. We repeat the production function estimations assuming a less flexible, but more traditional, Cobb-Douglas functional form. In addition, instead of estimating the production function parameters, we calibrate input elasticities to the average revenue shares within each industry (index function approach). In both cases, the estimates are comparable to the ones obtained by our flexible production function estimation approach, although less precisely estimated.

As explained in Section 2.2, when constructing a firm-level price index, one needs to take a stance on how to aggregate the prices across the heterogeneous products produced by a firm. In our baseline specification, we follow the consumer preference-based price index (CUPI) approach proposed by Redding and Weinstein (2020). In Appendix F, we show that the estimated initial contraction, and subsequent rebound, of prices following the financial shock is also evident when one uses alternative price measures. In particular, we show that our results are robust to constructing the firm-level price index as the revenue-share weighted average of product-level prices. Moreover, our results are also robust to using just the price of the main product of the firm (defined as the product with the highest revenue share), which does not require taking a stance on aggregation across different products.

5 Understanding the productivity and pricing effects of financial shocks

Having decoupled the effects of financial shocks on firm's productivity growth and pricing policies, we now provide evidence regarding the economic mechanisms underlying both responses. We show that in the immediate aftermath of the financial shock firms take actions to counteract the liquidity shortage that arose due to the drop in external financing. We document that producers reduce output prices in an attempt to increase cash flows from the product market by liquidating their existing stock of final goods. At the same time, firms exposed to the shock reduce operating costs by cutting expenditures on investments in innovation, which explains the persistent, but delayed, negative impact on long-run productivity growth. This productivity slowdown, combined with the increase in financing costs, explains the long-run increase in prices, as increases in the cost of production are passed-through to customers.

5.1 Understanding the transmission of financial shocks to productivity growth

Innovation in production processes, human capital accumulation, and organizational changes are the engine of firms' productivity growth (Syverson, 2011).[23] The availability of external financing plays a central role in this process. Like any form of investment, innovation requires financing (Kerr and Nanda, 2015; Howell, 2017). Unlike other forms of (tangible) investments, intangible assets typically provide poor collateral to creditors, and therefore lenders are less willing to finance them during periods of credit market distress (Shleifer and Vishny, 1992). Moreover, investments in intangibles tend to have more unpredictable and delayed returns (Caggese, 2012).[24] Therefore, relative to other forms of investments, productivity-enhancing investments are among the first category of expenses cut by firms coping with a tightening of credit supply conditions (Almeida and Campello, 2007).

The data provide strong support in favor of the hypothesis that the transmission of financial shocks to firms' productivity growth operates through an innovation channel. We first show that firms cut investments in innovation in response to the credit supply shock. We then provide evidence linking these reductions in investments in innovation to sizable contractions of long-run productivity growth.

Innovation response to financial shocks. Using the information reported in the AA, we compute three indicators of firm expenditures on productivity-enhancing activities. First, for each year following the burst of the sovereign crisis, we compute the R&D investment rate (Inv. Rate R&D$_\tau$), which is the ratio of cumulative expenses on R&D

[23] Garcia-Macia (2017), Huber (2018), Anzoategui et al. (2019) highlight that reduced investments in intangible assets over time can lead to a slowdown of firms' productivity growth. Bloom et al. (2013) emphasizes the role of information technology investments and organizational capital in generating productivity increases at the firm level.

[24] See also Castro, Clementi, and Lee (2015) for evidence connecting innovation-related activities and increases in the volatility of productivity growth.

up to year 2009+τ ($\tau = \{1, ..., 7\}$) scaled by the stock of intangible assets in 2009. Our second indicator is a dummy variable that flags firms investing any positive amount in R&D in a given year (Any R&D Expense$_\tau$). This variable captures the extensive margin of innovation, accounting for the lumpy nature of R&D investments. Our third indicator recognizes that innovation spurs from R&D as long as a skilled and appropriately trained workforce is capable of integrating new technologies into the existing production processes (Hall and Lerner, 2010). To capture this aspect, we gather information on employee training expenditures (Training Expenses$_\tau$). Specifically, we calculate cumulative average training expenditures per employee scaled by expenditures per employee in year 2009.

Table 3 shows that firms more exposed to the credit supply shock reduce investments in innovation and training more than less exposed counterparts. For a few years after the burst of the sovereign crisis, firms borrowing from lenders more exposed to distressed sovereigns display a widening innovation gap. We estimate that, on average, a one standard deviation increase in lenders' exposure to the distressed securities translates into a drop of about 3 percent in the R&D investment rate after one year, and a reduction of up to 59 percent in the cumulative R&D investment rate four years later (column 1). The effect of the credit contraction is also evident if one looks at the extensive margin of R&D investments (column 2). We estimate that a one standard deviation increase in exposure to the shock leads, on average, to a reduction of over 4 percentage points in the probability of devoting any resources to R&D in the year after the shock, and this effect persists. Investments in human capital are also affected (column 3). Comparing two producers with a one standard deviation difference in lenders' exposure to the shock, we observe that the more exposed one cuts expenditures on training by about 20 percent more per employee. The effect on training is more transitory relative to the estimated effects on R&D.

These results are in line with those documented in recent papers (Manaresi and Pierri, 2018; Duval, Hong, and Timmer, 2020), suggesting that the contraction in credit supply reduces productivity growth because it forces firms to cut investments in productivity-enhancing activities. They are also consistent with Caggese (2019), which provides evidence linking financial frictions and productivity growth over a firm's life cycle through the impact that such frictions have on the ability to sustain more radical innovation.

Impact of innovation expenditures on productivity growth. We take our analysis one step further and provide direct evidence connecting the availability of external financing, productivity-enhancing activities, and productivity growth. Mirroring model (5), we run a sequence of 2SLS regressions at different horizons:

$$\Delta_\tau \ln TFPQ_j = \alpha_\tau \cdot \Delta_1 Z_j + \Gamma'_{K,\tau}\mathbf{K}_j + \Gamma'_{X,\tau}\mathbf{X}_j + i_{ind,\tau} + i_{reg,\tau} + u_{j\tau}. \tag{6}$$

The left-hand-side variable measures the *cumulative* growth rate of TFPQ between the year 2009 and year 2009 + τ, $\tau = \{1, ..., 7\}$. The (endogenous) regressors of interest, $\Delta_1 Z_j$, measure changes in investments in innovation from 2009 to 2010 (R&D and training expenditures), which we have just shown are affected by the contraction in credit supply. These changes in investments are instrumented with our credit supply shock (Shock_j) in order to isolate variation in expenditures that is driven by firms' differential exposure to the credit tightening. This estimation approach allows us to tease out the credit supply driven connection between two endogenous variables (productivity and investments), whose covariation could otherwise be determined by factors other than the availability of external financing.

Table 4 reports 2SLS estimates over different horizons. The innovation gap materializes into lower productivity growth, as evidenced by the positive estimated coefficients. The timing of the effect is as relevant as its direction. A contraction of productivity-enhancing investments, driven by the lack of financing possibilities, is not felt immediately but rather materializes into a productivity slowdown in the medium-long run. For example, we estimate that a one percentage point reduction in the R&D investment rate in 2010 translates into a reduction of productivity growth of over 3 percent six years later. Similarly, a reduction in training expenses per employee by one percent translates into 0.8 percent lower productivity growth six years later. These results offer direct evidence of the link between productivity growth and firms' decisions to innovate. More specifically, the delayed and persistent productivity response documented by our analysis helps rationalize the slow economic recovery observed after episodes of the financial crisis.[25]

[25]See, among others, the evidence in Cerra and Saxena (2008), Jordà, Schularick, and Taylor (2013), Reinhart and Rogoff (2014), and Hall (2015).

We note that the connection between financial shocks and firm-level productivity dynamics could also operate through other channels besides the investment channel. While we do not directly test these alternative theories, our earlier results from Table 2 offer insights regarding their empirical relevance. In light of the negative long-run response of productivity growth, we can rule out economic channels predicting that a tightening of external financing conditions might spur productivity growth because, for example, it forces firms to cut production slackness (Field, 2003) or be more selective in their investment projects (Jensen, 1986). The timing of the TFPQ response further narrows down the set of channels that produce predictions consistent with the data. Specifically, our findings are inconsistent with the hypothesis that financial shocks affect firms' technical efficiency because they force firms to inefficiently use their resources, for example because a lack of working capital impedes certain input purchases, or because the shock shifts managers' attention towards seeking alternative sources of financing and away from maximizing efficiency. In fact, in both cases, one would expect to see an immediate productivity effect that gradually fades away as firms regain access to credit markets, which is the opposite of what our TFPQ estimates indicate.

5.2 Understanding the price response to financial shocks

The results in Section 4 show that the financial shock not only impacted long-run productivity growth via a reduction in investments in innovation, but also led to sizable adjustments in firms' pricing policies, both in the short- and long-run. We now examine why firms adjust their pricing behavior in response to a tightening of credit supply conditions, as well as why these responses differ depending on the horizon. We begin by discussing the economic forces driving the long-run price adjustment and then move to the ones behind the short-term adjustment.

Long-run price adjustment. Figure 3 shows that three years after exposure to the credit supply shock, more exposed producers charged higher prices relative to less exposed ones, and this effect remained roughly constant over the rest of our sample. One natural explanation for this is that the shock eventually led to an increase in production costs, and firms passed this through to consumers. The empirical analysis presented so far provide two pieces of evidence to support this idea.

First, as shown in Section 3, firms were eventually able to compensate for the contraction in credit, but only by tapping into more expensive alternative sources. Second, we have also shown that financial shocks set firms on a lower (long-run) productivity growth path. To the extent that firms pass through efficiency gains to consumers in the form of lower prices, firms more affected by the credit shock will price at a higher level relative to similar, less affected firms. Finally, the timing of both the increase in borrowing costs and the decrease in productivity line up with the timing of the price increase, lending further support to these explanations.

Previous studies have emphasized how supply side shocks—such as productivity innovations and changes in input prices—are passed-through to output prices, generating a muted, or even opposite, response of TFPR relative to TFPQ (Foster, Haltiwanger, and Syverson, 2008; Foster, Haltiwanger, and Syverson, 2016; Moreira, 2020). Our analysis indicates that similar forces can also explain long-run price dynamics (and thus the implied TFPR-TFPQ bifurcation) following episodes of financial market distress, emphasizing the important role played by the availability and cost of external finance for firms' production and pricing decisions.

Short-run price adjustment. In contrast to the long-run increase in prices, in the short-run we find that firms affected by the credit crunch reduce their prices. We show that this adjustment can be explained by firms using low pricing as a source of internal finance in an effort to counterbalance the drop in external financing. Appendix D presents a theoretical framework, based on an extension of Hendel (1996), that rationalizes this behavior.[26] Intuitively, in the presence of financial frictions, a sudden tightening of credit supply deprives firms of access to credit, thereby increasing the risk of financial distress. Recognizing the increased value of liquidity, firms have the option to increase cash flows by liquidating assets (e.g., plants, machinery) or reducing operating costs. However, the former might not be time-effective or might not generate sufficient cash flows if liquidation takes place at fire-sale prices.[27] The latter, reducing operating costs (e.g., firing workers), may be unfeasible and equally slow to implement.[28] Reducing expenditures on investments in intangibles is another possibility. However, as we have shown in Section

[26]See also Kim (2020).

[27]Shleifer and Vishny (1992) show that assets can become non-liquid when a firm is in financial distress since its competitors (the potential buyers of the assets) are likely to be as well.

[28]Belgium has fairly extensive protective labor laws, which limits the ability of firms to downscale their labor force. Moreover, collective bargaining plays a very important role in shaping employment compensations in Belgium, thereby preventing firms from adjusting hourly compensations.

5.1, it can have severe long-term consequences for firm productivity and thus firm value.

An alternative option for firms is to use low pricing as way to raise liquidity from the product market. As we illustrate in Appendix D, while lowering output prices might be sub-optimal in normal circumstances, the change in pricing behavior can help firms generate additional cash flows by selling off their existing stock of finished goods.

As a first piece of evidence for this hypothesis, we show that producers that were more likely to be impacted by the credit crunch are those that display sharper adjustments of their pricing policies. Table 5, panel a, studies the short-term price response ($\Delta_1 \ln P_j$) to the credit shock as a function of firms' reliance on bank financing. Column 1 shows that firms that entered the crisis with higher leverage—the ratio of bank debt to total assets at the end fiscal year 2009—reduced prices more aggressively when coping with the credit crunch. Columns 2 and 3 display the heterogeneous pricing response as a function of the firm's likelihood of financial distress, measured by the Z-score at the end of fiscal year 2009.[29] We find that the price reduction is increasing in the likelihood of financial distress (i.e., a lower Z-score). Importantly, the credit shock had no impact on the pricing behavior of firms that entered the sovereign crisis with very low likelihoods.

In addition, as documented by Kim (2020), firms with higher levels of existing inventories should be better able to exploit low pricing as a form of liquidity management, as liquidating existing inventories does not involve incurring additional production costs.[30] We find strong support for this prediction in the data. First, in Appendix F we document that firms borrowing from legacy lenders with larger sovereign holdings did indeed reduce inventories in the immediate aftermath of sovereign shock relative to less exposed firms. Moreover, this response is primarily driven by those producers that entered the crisis with larger inventory holdings.

Second, we show that firms differ in their ability to use low pricing as a source of internal finance based on their level of inventory holdings. Table 5, panel b, shows that firms that can count on larger inventory stocks to liquidate are those who more aggressively cut output prices in response to the credit shock (column 1). A one standard

[29]The Z-score (Altman, 1968) is the output of a credit-strength test that gauges a company's likelihood of bankruptcy. A score below 1.8 signals the company is likely headed for bankruptcy, while a score above 2.9 signals a very low likelihood of financial distress. See Appendix A for additional details on the construction of the Z-score.

[30]Previous work has shown that liquidity constrained firms also shed inventories in response to demand and monetary policy shocks. See, e.g., Gertler and Gilchrist (1994) and Kashyap, Lamont, and Stein (1994).

deviation increase in exposure to the shock leads to a contraction of output prices that is more than twice as large for a firm that had 27 cents worth of inventories per euro of assets (the 75th percentile) relative to a firm that had 9 cents worth of inventories per euro of assets (the 25th percentile). Underscoring the external validity of the analysis, we note that our estimates are consistent in both direction and magnitude with those reported in Kim (2020), estimated using consumer price data for a sample of US firms whose lenders were differentially exposed to the Lehman Brothers' default.

Finally, an additional testable implication of the hypothesis that firms use low pricing as a source of internal finance comes from the relationship between pricing behavior and product market conditions. The extent to which producers can expand their customer base and increase sales by lowering output prices depends on the price sensitivity of demand, which is affected by the ability of consumers to substitute the output of one supplier for another (Syverson, 2004).[31] Since more concentrated markets are characterized by a lower degree of product substitutability, we use the market share of the largest producers in an industry as a proxy of the residual demand elasticity faced by producers in that industry. Specifically, we use the complement of the market shares (i.e., one minus the shares) of the top 5 and top 10 producers in narrowly defined industries (3-digit industry codes), measured at the end of the fiscal year 2009. We denote these variables by Demand Elasticity^k, $k = 5, 10$. High values of these variables denote industries where producers can more easily induce customers to substitute competitors' products for their own by implementing more aggressive pricing policies. Columns 2 and 3 of Table 5 show that firms that operate in more price elastic industries are more likely to reduce prices in response to the shock. Comparing firms at the 25th and 75th percentile of the distribution of industry-level shares of the top 5 (top 10) producers, our estimates imply a price contraction that is about three to four times as large as the contraction observed in less concentrated industries.[32]

[31]"Markets with greater substitutability are more competitive in the sense that their higher cross-price elasticities more greatly reward (punish) relatively low- (high-) cost producers in terms of market share." (Syverson 2004, page 1187). The theoretical framework in Appendix D formalizes the idea that price elasticities affect a firm's ability to leverage low pricing as a way to raise liquidity.

[32]The 25th and 75th percentiles of the distribution of industry-level shares of top 5 (top 10) producers are 22 percent (32 percent) and 60 percent (73 percent).

6 The link between the productivity and price effects of financial shocks

The results presented thus far provide important insights into how firms respond to credit supply shocks. Since an unexpected tightening of external financing conditions increases the likelihood of financial distress, firms take actions to increase liquidity. Specifically, we showed that firms pursue more aggressive pricing strategies to increase cash flows from the product market as well as cut costs by reducing expenditures on investments in innovation and worker's human capital. Because these two actions are substitutable for the purpose of freeing up liquidity, it seems natural to ask whether firms that are better able to reduce prices are able to reduce investments in innovation less, thus helping to mitigate the long-run effect on productivity growth. In this section we provide direct evidence for this hypothesis, showing that the price and productivity effects of financial shocks are in fact linked.

6.1 Non-parametric evidence

We begin by documenting a statistical relationship between the causal effect of financial shocks on pricing policies in the short-run and the causal effect of the shock on productivity growth in the long-run. We first compute the contribution of each firm to the average short-term price effect ($\hat{\beta}_1$) and the average long-run TFPQ growth effect ($\hat{\beta}_7$) reported in columns 3 and 4 of Table 2, respectively.[33] We then group firms into percentiles based on their contribution to the short-term pricing response. The binned scatter plot in Figure 5, panel a shows the average contribution to the long-term TFPQ response (y-axis) within each group of firms, sorted by to their contribution to the short-term pricing response (x-axis). This exercise reveals a strong negative correlation between firms' short-term price response and their long-term productivity growth response (the correlation coefficient is -0.214, significant at the one percent level). This suggests that firms that endogenously respond to the financial shock by pricing more aggressively are the ones that experience, in the long-run, a less pronounced contraction of physical

[33]The contribution of each firm to the average short- and long-run treatment effects ($\hat{\beta}_\tau$, $\tau = 1, 7$) of productivity and prices are obtained using the influence function method (Cook and Weisberg, 1982). We rescale the influence functions so that the average contribution across observations (firms) equals the estimated treatment effects at each horizon.

productivity growth.

It is important to note that the revenue productivity estimates are unable to detect the inter-temporal relationship between the price and productivity responses to the financial shock, casting further doubt on inferences based on TFPR movements. Panel b and panel c in Figure 5 demonstrate this. We repeat the exercise of panel a using the two TFPR measures of the long-term productivity response instead. Because firms affected by the shock eventually increase prices, the revenue productivity estimates suggest either a null or even a positive relationship between short-term price adjustments and long-run productivity implications.

6.2 Short-term pricing response and long-run productivity growth

We now provide evidence that the economic mechanism connecting the short-run price reductions to long-run productivity growth operates through investments in innovation. In Section 5, we showed that firms with larger pre-shock inventory levels and those facing more elastic demand for their products decreased their prices more in response to the shock, consistent with the idea that firms leveraged the product market to help deal with the drop in external finance. Thus, we should expect firms with a greater ability to reduce prices in the short-run to be less able to reduce investments in innovation in response to the shock. To test this hypothesis, we examine how the effect of the shock on investments in productivity enhancing activities (R&D and training) varies with a firm's inventories and the product market conditions.

We find significant heterogeneity in the effect of the credit shock on firms' expenditures on productivity-enhancing activities (Table 6). Firms that can rely on a larger stock of inventories to liquidate and those operating in industries where demand is more sensitive to price changes are the ones that display a smaller contraction of both innovation expenses and investments in workers' human capital. Comparing firms at the 25th and 75th percentile of inventories and price elasticity measures, we find that firms that were better able to reduce prices in response to the shock (i.e., those with higher inventory levels and those facing more elastic demand) reduce their investments in innovation by between 30 percent and 80 percent less.

Finally, we show that the ability to reduce prices more, and thus reduce investments in intangibles less, translates into significantly lower contractions in long-run productivity. In Table 7 we examine the heterogeneous response of long-term productivity growth as a function of firms' inventories and demand elasticity. Consistent with the evidence provided by the non-parametric exercise in Figure 5, the coefficients in Table 7 indicate that firms with a greater ability to adjust prices in response to a financial shock systematically experience a lower contraction of long-run productivity growth in response to the shock. To put our estimates into perspective, we compute the long-run effect of a one standard deviation increase in exposure to the credit shock comparing firms that differ in their ability to respond by pricing more aggressively (25th vs 75th percentile of the distribution of inventories and demand elasticity). This exercise shows that firms with larger stocks of inventories and those that operate in more price-elastic industries experience a contraction in TFP growth that is about 25 percent smaller.

7 Conclusions

This paper sheds new light on the nexus between financing frictions and firm-level productivity growth. Using detailed administrative records on firm-level output prices and quantities, combined with quasi-experimental variation in credit availability, we systematically explore the relationship between a tightening of financing conditions and firm productivity growth, emphasizing the crucial role played by firm price adjustments in quantifying and understanding this relationship.

By disentangling the pricing and productivity effects, we document that financial shocks have no immediate effect, but a substantial, delayed, and persistent long-run impact on firm-level technical productivity growth. The reason, we show, is that a tightening of external finance conditions leads to a contraction of investments in intangible assets, such as R&D and worker human capital, which sets firms on a lower productivity growth path. Importantly, because firms adjust their pricing policies to cope with the shock, we also document that revenue-based productivity measures provide biased estimates and possibly misleading predictions regarding the implications of financial shocks on firm productivity, both in the short- and long-run.

These results have important welfare implications. For one, they corroborate the hypothesis that the slow economic recovery observed after episodes of financial market distress is driven (at least in part) by a slow-down of firm-level productivity growth, and highlight that the impact of this channel on long-run growth is more pronounced and longer-lasting than previously understood. For another, the long-run increase in output prices, driven by the pass-through of financial costs and by the productivity slowdown, further exacerbates the impact of financial shocks on consumers.

This study also highlights that understanding and accounting for the endogenous price response to financial shocks goes beyond measurement considerations. Financial shocks jeopardize a firm's capacity to sustain productivity growth through investments in innovation and human capital. The ability to generate additional cash flows via the product market through low pricing allows firms to mitigate this effect, thereby softening the long-run impact of the shock on productivity. This new mechanism highlights that the nominal and real impacts of financial shocks are more interrelated than previously recognized. The connection between the behavior of firms in product markets and productivity growth is an active area of research. It has been shown, for example, that product market conditions shape aggregate productivity through misallocation effects and firm selection (see, e.g., Restuccia and Rogerson, 2017 and Syverson, 2004). This paper offers new insights that further connect the two by showing that firms' actions in product markets can help mediate the effect of financial shocks on within-firm productivity growth.

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Table 1: Summary statistics

Panel a: Growth rates

	Short-term		Long-term	
	Mean	SD	Mean	SD
$\Delta Credit$	-0.146	0.568	-0.631	1.073
Δfc	0.002	0.120	-0.001	0.156
$\Delta \ln TFPR^{\mathrm{R}}$	0.023	0.114	0.026	0.150
$\Delta \ln TFPR^{\mathrm{Q}}$	0.057	0.144	0.130	0.173
$\Delta \ln TFPQ$	0.052	0.189	0.054	0.384
$\Delta \ln P$	0.005	0.186	0.076	0.348

Panel b: Investment variables

	Short-term		Long-term	
	Mean	SD	Mean	SD
Inv rate R&D	0.109	0.359	2.974	9.103
Any R&D Expense	0.165	0.372	0.196	0.397
Training Expenses	0.487	1.699	1.288	2.769

Panel c: Firm characteristics

	Mean	SD
(Credit Supply) Shock	0.142	0.046
Total Assets (Million Euros)	90.948	321.767
Bank Leverage	0.208	0.196
Inventories	0.191	0.129
Demand Elasticity$^{\mathrm{Top5}}$	0.582	0.223
Demand Elasticity$^{\mathrm{Top10}}$	0.468	0.231
Z-score	2.062	1.096

Notes: This table reports the summary statistics of the main variables used in the empirical analysis. Panels a and b focus on outcome variables. In panel a, we present the short-term growth rates (2009-2010) and long-term growth rates (2009-2016) of credit balances, financing costs, the measures of productivity, and prices. In panel b, we report short-run (2010) and long-term cumulative (2010-2016) investment variables. Panel c focuses on variables that are used as regressors in the empirical models. The variables in panel c are measured prior to the Greek bailout (that is the end of fiscal year 2009 for the variables coming from the AA, and the end of 2010:Q1 for our credit supply shock measure). In our empirical analysis, we de-mean and scale the credit supply shock measure by its standard deviation.

Table 2: Response of productivity and prices to negative credit supply shocks

	$\Delta_\tau \ln TFPR^{R}$	$\Delta_\tau \ln TFPR^{Q}$	$\Delta_\tau \ln TFPQ$	$\Delta_\tau \ln P$
	(1)	(2)	(3)	(4)
$\hat{\beta}_1$	-0.015***	-0.018***	0.001	-0.018**
	(0.005)	(0.004)	(0.010)	(0.008)
$\hat{\beta}_2$	-0.018**	-0.012	-0.017	0.004
	(0.007)	(0.008)	(0.011)	(0.009)
$\hat{\beta}_3$	-0.021**	-0.025***	-0.058***	0.033**
	(0.009)	(0.009)	(0.014)	(0.015)
$\hat{\beta}_4$	-0.040***	-0.047***	-0.084***	0.037**
	(0.008)	(0.008)	(0.021)	(0.017)
$\hat{\beta}_5$	-0.032***	-0.037**	-0.082***	0.040*
	(0.010)	(0.018)	(0.026)	(0.0213)
$\hat{\beta}_6$	-0.032***	-0.026***	-0.067***	0.040*
	(0.011)	(0.012)	(0.020)	(0.023)
$\hat{\beta}_7$	-0.043***	-0.049**	-0.085***	0.036*
	(0.012)	(0.013)	(0.024)	(0.021)

Notes: This table reports the estimates of the effect of the credit supply shock on the cumulative growth rate of TFPR, TFPQ, and prices estimated using model (5). All regressions include bank-level controls, firm-level controls, industry fixed effects, and region fixed effects. Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 3: Response of R&D investments and employee training to negative credit supply shocks

	Δ_τProductivity-enhancing activities		
	Inv rate R&D (Cumulative)	Any R&D Expense	Training Expenses (Cumulative)
	(1)	(2)	(3)
$\hat{\beta}_1$	-0.030**	-0.041***	-0.200***
	(0.014)	(0.015)	(0.078)
$\hat{\beta}_2$	-0.096***	-0.024	-0.003
	(0.020)	(0.024)	(0.087)
$\hat{\beta}_3$	-0.321***	-0.077***	0.154
	(0.084)	(0.018)	(0.103)
$\hat{\beta}_4$	-0.592***	-0.045*	0.125
	(0.194)	(0.026)	(0.129)
$\hat{\beta}_5$	-0.463	-0.045	0.114
	(0.329)	(0.029)	(0.150)
$\hat{\beta}_6$	-0.323	-0.028	0.227
	(0.525)	(0.032)	(0.192)
$\hat{\beta}_7$	-0.593	0.008	0.328
	(0.478)	(0.033)	(0.192)

Notes: This table reports the estimates of the effect of the credit supply shock on investments in R&D and employee training expenses using the model in (5). In column 1, the dependent variable is the cumulative innovation rate, measured as the cumulative expenses in R&D between the end of fiscal year 2009 and the end of fiscal year $2009 + \tau$ ($\tau = \{1, ..., 7\}$), scaled by the book value of intangible assets in 2009. In column 2, the dependent variable is a dummy variable measuring whether the firm reported any R&D expenses in fiscal year $2009 + \tau$. In column 3, the dependent variable is the cumulative training expenditures per employee between the end of fiscal year 2009 and year $2009+\tau$. All regressions include bank-level controls, firm-level controls, industry fixed effects, and region fixed effects. Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 4: Effect of credit supply driven contraction of productivity-enhancing activities on TFPQ growth

	$\Delta_\tau \ln TFPQ$						
	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 4$	$\tau = 5$	$\tau = 6$	$\tau = 7$
Inv Rate R&D	0.083	0.680	2.111**	2.849*	3.690	2.177**	3.271*
	(0.345)	(0.462)	(0.961)	(1.580)	(2.448)	(0.951)	(1.622)
Any R&D Expense	0.056	0.505	1.539**	1.704**	1.953*	1.495**	1.817***
	(0.226)	(0.320)	(0.631)	(0.742)	(0.976)	(0.647)	(0.575)
Training Expenses	-0.070	0.059	0.490	0.797	0.566*	0.536*	0.797*
	(0.064)	(0.103)	(0.396)	(0.488)	(0.281)	(0.303)	(0.440)

Notes: This table reports the 2SLS estimates capturing the effect of variation in R&D and training expenses in the aftermath of the credit supply shock, instrumented with the credit supply shock, on cumulative TFPQ growth over different horizons. In the first regression model, the endogenous regressor is the cumulative innovation rate, measured as the expenses in R&D during fiscal year 2010 scaled by the book value of intangible assets in 2009. In the second regression model, the endogenous regressor is a dummy variable measuring whether the firm reported any R&D expense in fiscal year 2010. In the third regression model, the endogenous regressor is cumulative training expenditures per employee in fiscal year year 2010. In accordance with equation (6), all regressions include bank-level controls, firm-level controls, industry fixed effects, and region fixed effects. Standard errors are clustered at the main-lender level and reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 5: Heterogeneity in the short-term price response

	Short-term $\Delta \ln P$		
Panel a: Likelihood of financial distress			
	(1)	(2)	(3)
Shock	-.009	-.040***	-.026***
	(.009)	(.012)	(.009)
Shock × Bank Leverage	-.045*		
	(.023)		
Shock × Z-score		.010***	
		(.004)	
Shock × Safe			.035***
			(.011)
R-squared	.061	.063	.063
Observations	1024	1024	1024
Panel b: Inventory holdings and demand elasticity			
	(1)	(2)	(3)
Shock	-0.003	0.006	0.005
	(0.009)	(0.015)	(0.012)
Shock × Inventories	-0.081***		
	(0.031)		
Shock × Demand Elasticity^{Top5}		-0.035*	
		(0.020)	
Shock × Demand Elasticity^{Top10}			-0.039*
			(0.020)
R-squared	0.063	0.063	0.064
Observations	1024	1024	1024

Notes: This table reports the estimates of the heterogeneous short-term effect ($\tau = 1$) of the credit supply shock on prices, estimated using model (5) and augmented to include interactions between the shock variable and various variables. In panel a, the interacted regressors are bank leverage (bank debt over assets) and measures of the likelihood of financial distress (the Z-score and a dummy identifying firms with very low likelihood of distress, i.e., a Z-score higher than 2.9). In panel b, the interacted regressors include the inventory stock of finished goods and measures of demand elasticity. The interacted regressors themselves are also included in the regression model. All regressions include bank-level controls, firm-level controls, industry fixed effects, and region fixed effects. Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 6: Heterogeneous short-term response of productivity-enhancing activities

	Short-term Δ Productivity-enhancing activities								
	Inv Rate R&D (1)	Any R&D Expenses (2)	Training Expenses (3)	Inv Rate R&D (4)	Any R&D Expenses (5)	Training Expenses (6)	Inv Rate R&D (7)	Any R&D Expenses (8)	Training Expenses (9)
Shock_j	-0.051***	-0.082***	-0.294***	-0.113***	-0.078***	-0.745***	-0.104***	-0.080***	-0.637***
	(0.017)	(0.024)	(0.076)	(0.032)	(0.022)	(0.164)	(0.028)	(0.021)	(0.146)
Shock × Inventories	0.104**	0.192*	0.465***						
	(0.049)	(0.095)	(0.110)						
Shock × Demand $\text{Elasticity}^{\text{Top5}}$				0.116**	0.042**	0.755***			
				(0.047)	(0.024)	(0.190)			
Shock × Demand $\text{Elasticity}^{\text{Top10}}$							0.129***	0.058**	0.742***
							(0.050)	(0.027)	(0.196)
R-squared	0.048	0.083	0.035	0.055	0.080	0.055	0.056	0.081	0.054
Observations	775	775	703	775	775	703	775	775	703

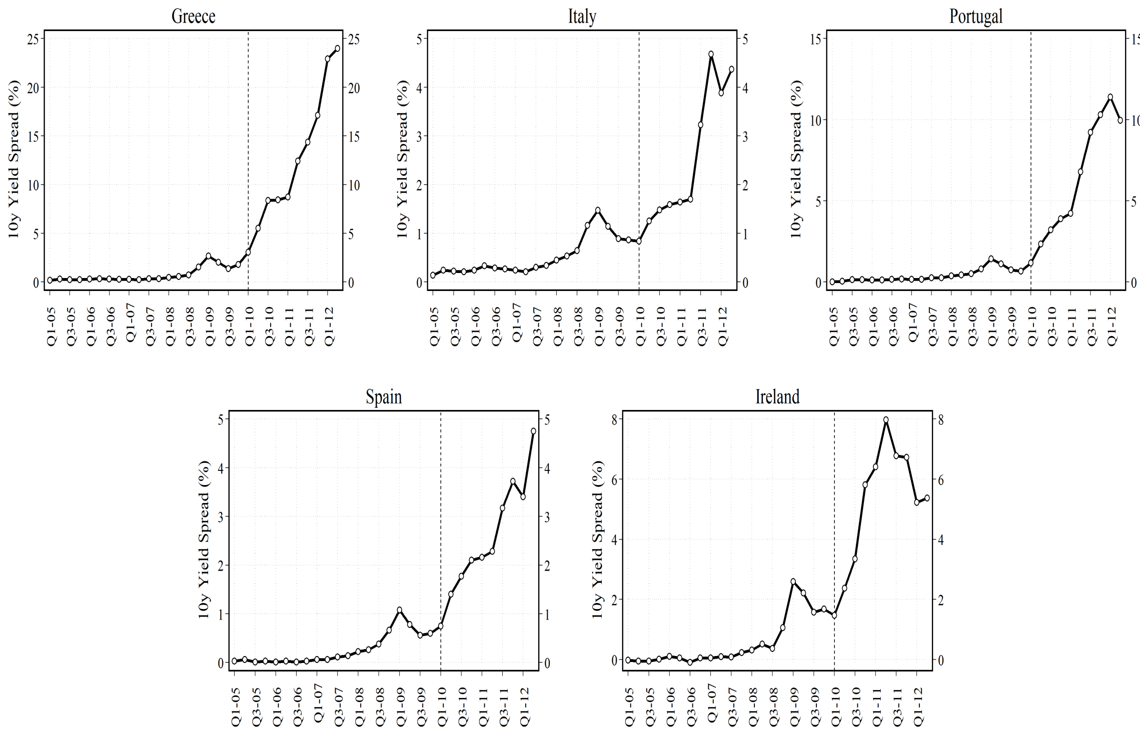
Notes: This table reports the estimates of the heterogeneous short-term effect ($\tau = 1$) of the credit supply shock on our measures of investments in productivity-enhancing activities, estimated using model (5), and augmented to include an interaction between the shock variable and the inventory stock of finished goods and measures of demand elasticity. All regressions include bank-level controls, firm-level controls, industry fixed effects, and region fixed effects. Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 7: Heterogeneous long-term response of productivity growth

	Long-term $\Delta \ln TFPQ$		
	(1)	(2)	(3)
Shock$_j$	-0.123***	-0.142***	-0.127***
	(0.028)	(0.032)	(0.028)
Shock × Inventories	0.165***		
	(0.064)		
Shock × Demand Elasticity$^{\text{Top5}}$		0.067**	
		(0.031)	
Shock × Demand Elasticity$^{\text{Top10}}$			0.054*
			(0.030)
	Heterogeneous Effects		
Lower ability to adjust prices	-0.109***	-0.117***	-0.115***
	(0.025)	(0.026)	(0.025)
Higher ability to adjust prices	-0.082***	-0.091***	-0.091***
	(0.024)	(0.024)	(0.024)
Difference Lower-Higher ability	-0.027**	-0.026**	-0.024*
	(0.010)	(0.012)	(0.013)
R-squared	0.074	0.074	0.074
Observations	652	652	652

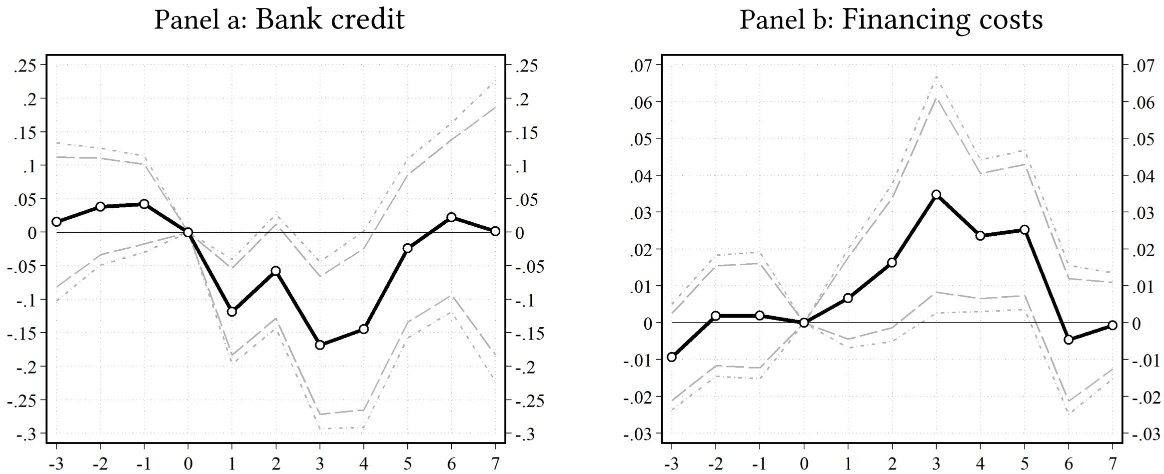
Notes: This table reports the estimates of the heterogeneous long-term effect ($\tau = 7$) of the credit supply shock on physical productivity growth (TFPQ), estimated using model (5), and augmented to include an interaction between the shock variable and the inventory stock of finished goods and measures of demand elasticity. Below the coefficient estimates we report the estimated effects evaluated at the 25th and 75th percentiles of the price shifters, as well as the difference between the two. All regressions include bank-level controls, firm-level controls, industry fixed effects, and region fixed effects. Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Figure 1: Sovereign yield spread of GIPSI countries after the Greek bailout



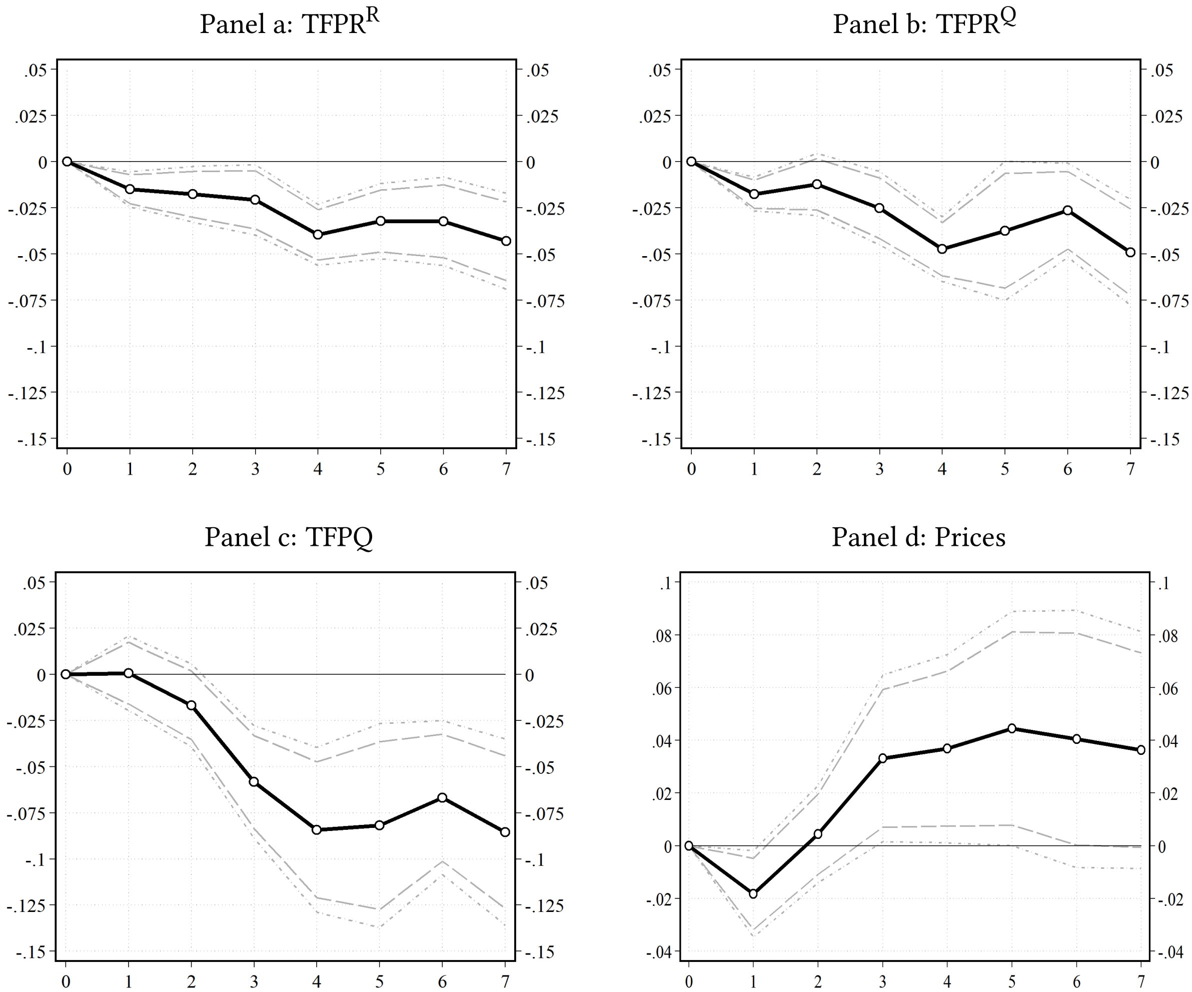
Notes: Figure 1 displays the time-series evolution of the spread between the yield to maturity of 10-year sovereign bonds issued by GIPSI counties (Greece, Italy, Portugal, Spain, Ireland) and the yield to maturity of 10-year sovereign bonds issued by Germany. The vertical line marks the last quarter before the Greek bailout request (2010:Q1).

Figure 2: Exposure to the sovereign shock and credit market outcomes



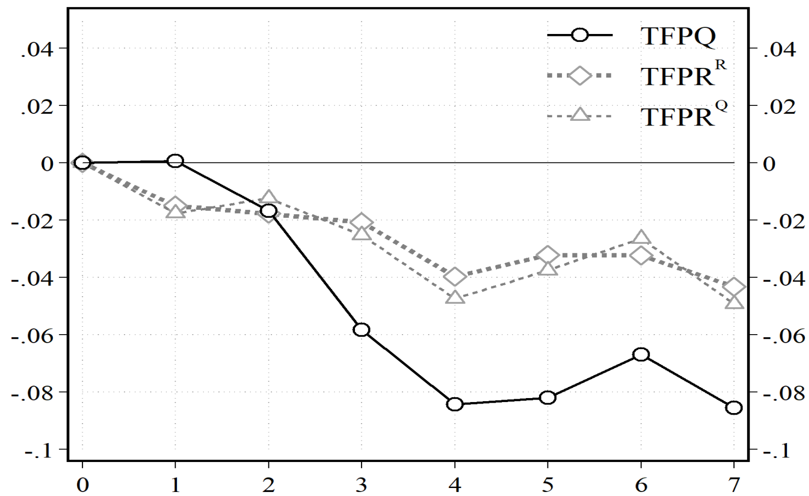
Notes: Figure 2 explores the relationship between firms' exposure to the sovereign shock via their lenders and the growth rate of bank credit and change in financing costs. It reports the estimates of coefficients β_τ from model (5) where the left-hand side variables are the firm-level growth rate of credit (Panel a) and the firm-level change in financing costs (Panel b). The dashed lines depict 90 percent confidence intervals and the dotted lines depict 95 percent confidence intervals based on the estimated clustered standard errors.

Figure 3: Response of productivity and prices to negative credit supply shocks



Notes: This figure accompanies Table 2, plotting the coefficient estimates and associated confidence intervals. The solid lines depict the point estimates; the dashed lines depict 90 percent confidence intervals and the dotted lines depict 95 percent confidence intervals based on the estimated clustered standard errors.

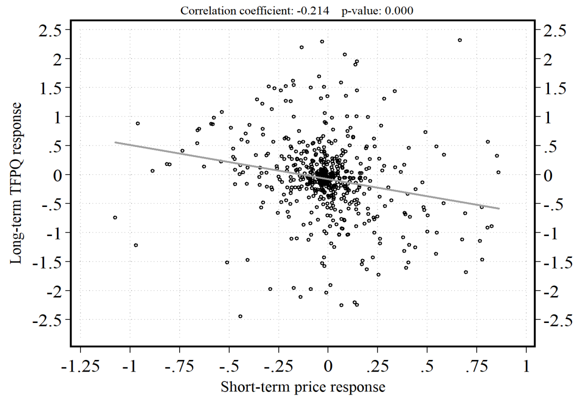
Figure 4: Comparison of the TFPQ and TFPR response to negative credit supply shocks



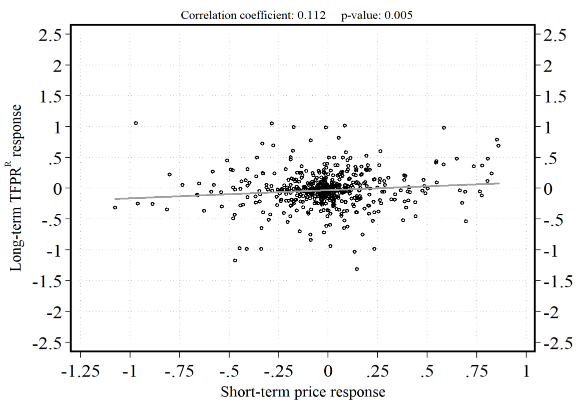
Notes: This figure accompanies Table 2. It compares the estimated cumulative response of the different productivity measures to the credit supply shock.

Figure 5: Linking the short-term price and long-term productivity response

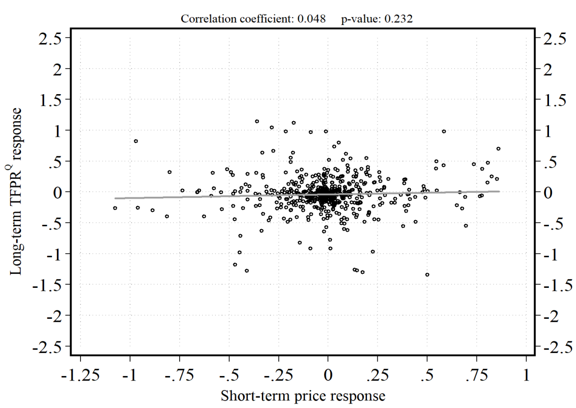
Panel a: TFPQ growth



Panel b: TFPR^R growth



Panel c: TFPR^Q growth



Notes: These binned scatter plots show the correlation between firms' short-term price and long-term productivity response to the financial shock. In each plot, a dot represents the average contribution to the productivity response (y-axis) and average contribution to price response (x-axis) of observations that belong to a given percentile of the distribution of the price and productivity response. The grey line is the best linear predictor of the long-run productivity effect given the short-term price effect.

Financial Shocks, Productivity, and Prices

Simone Lenzu, David A. Rivers, Joris Tielens

Online Appendix

A Data Appendix

In this appendix, we provide additional details on the source and definition of the variables used in the empirical analysis.

Firm-level variables. We denote by $\text{Credit}_{j,t}$ the firm-level outstanding bank credit balance (sum of term loans, credit lines, credit backed by receivables) from the CCR, which is constructed by summing across all lenders b of firm j in year t ($b \in \mathcal{B}_{j,t}$) , $\text{Credit}_{j,t} = \sum_{b \in \mathcal{B}_{j,t}} \text{Credit}_{jb,t}$. As in Chodorow-Reich (2014), we measure the τ-year cumulative growth in total bank credit of each firm as $\Delta_\tau \text{Credit}_j = \frac{\text{Credit}_{j,2009+\tau} - \text{Credit}_{j,2009}}{0.5(\text{Credit}_{j,2009+\tau} + \text{Credit}_{j,2009})}$, where $\text{Credit}_{j,2009}$ measures the average outstanding bank credit of firm j in the year prior to the burst of the sovereign crisis, and $\text{Credit}_{j,2009+\tau}$ measures the average outstanding credit τ-years afterwards. We measure average financing costs incurred during a year using information on financial charges and outstanding principal of financial debt from the firms' income statements and balance sheets as reported in the AA: $fc_{j,t} = \frac{\text{Financial Charges}_{j,t}}{\text{End of Year Financial Debt}_{j,t-1}}$. We then compute the change in the average financing costs relative to 2009, $\Delta_\tau fc_j = fc_{j,2009+\tau} - fc_{j,2009}$.

Section 2.2 and Appendices B and C describe how we construct our measures of price and productivity growth ($\Delta \ln TFPR^{\text{R}}$, $\Delta \ln TFPR^{\text{Q}}$, $\Delta \ln TFPQ$, and $\Delta \ln P$).

From the AA, we gather the following set of firm-level variables from firms' balance sheets and income statements: firm size (natural logarithm of total assets), bank leverage (bank debt outstanding over total assets), and stock of inventories of final goods (inventories of finished goods over total assets), all measured at the end of the fiscal year 2009. For each firm in our sample, we construct the Z-score at the end of fiscal year 2009 by adapting the Altman (1968) formula to private firms: Z-score = 3.107 × (EBIT / Total Assets) + 0.998 × (Sales / Total Assets) + 0.420 × (Capital / Total Liabilities) + 0.717 × (Working Capital / Total Assets) + 0.847 × (Retained Earnings / Total Assets).

Using the information reported in the AA, we compute three indicators of firm expenditures on productivity-enhancing activities. First, for each year following the burst of the sovereign crisis, we compute the R&D investment rate (Inv. Rate R&D_τ), which is the ratio of cumulative expenses on R&D up to year 2009+τ scaled by the stock of intangible assets in 2009: Inv. Rate R&D_τ = $\sum_{t=1}^{\tau}$ R&D $\text{Expenditures}_{2009+t}/\text{Intangible Assets}_{2009}$. Our second indicator is a dummy variable that flags firms investing any positive amount in R&D in a given year (Any R&D Expense_τ). This variable captures the extensive margin of innovation, accounting for the lumpy nature of R&D investments. Our third indicator recognizes that innovation spurs from R&D as long as a skilled and appropriately trained workforce is capable of integrating new technologies into the existing production processes. To capture this aspect, we gather information on employee training expenditures (Training Expenses_τ). Specifically, we calculate cumulative average training expenditures per employee scaled by expenditures per employee in year 2009: Training Expenses_τ = $\left(\sum_{t=1}^{\tau} \text{Training Expenditures}_{2009+t}/\tau\right)/\text{Training Expenditures}_{2009} - 1$.

Bank-level variables. We collect bank-level variables from confidential supervisory records of the National Bank of Belgium. The key variable of interest is banks' exposure to the sovereign crisis via their holdings of GIPSI sovereign securities—GIPSI Sovereigns_b = GIPSI Sovereign Holdings_b/Risk-weighted Assets_b in 2010:Q1—which is used to construct our firm-level credit supply shifter, as described in Section 3. We also gather information on a battery of bank-level characteristics which are included as controls in all econometric specifications. The set of bank-level variables includes bank size (natural logarithm of bank assets), variables capturing banks' funding structure (Tier 1 ratio, deposits over risk-weighted assets, net interbank liabilities scaled by risk-weighted assets), liquidity position (liquidity over risk-weighted assets), and quality of lending portfolio (non-performing loans over risk-weighted assets), measured before the shock (2010:Q1). Similar to our measure of GIPSI sovereign exposure, we aggregate these lender-specific variables to the firm-level by computing a weighted average across lenders using the share of firm j's credit received from each bank in the pre-shock period as weights.

Firm-bank-level variables. Exploiting the panel dimension of the CCR, we calculate length of the lending relationship (in quarters) between borrower j and bank b, $\text{Length of relationships}_{jb}$, measured as the number of consecutive quarters the relationship has been in place between 2006:Q1 and 2010:Q1. We subsequently aggregate across lenders and calculate the firm-level weighted average length of lending relationships as Length of relationships$_j$ = $\sum_{b \in \mathcal{B}_j} \omega_{jb} \times$ Length of relationships$_{jb}$, where ω_{jb} is the share of debt provided by each lender in 2010:Q1. We also compute the number of active lending relationships of each firm in the last quarter before the crisis (Number of relationships$_j$).

Comparison of firm characteristics. Table A.1 compares characteristics for the group of firms borrowing from banks with low GIPSI holdings (below the median of Shock$_j$) and the group of firms with high GISPI holdings (above the median of Shock$_j$), measured at the end of fiscal year 2009, before the burst of the sovereign debt crisis. Columns 1 and 2 report means and their standard errors (in parentheses). Column 3 reports the difference and standard errors (in parentheses) of a two-tailed test of equality of the means of the two groups. All firm variables are measured at the end of fiscal year 2009, the last quarter before the burst of the sovereign crisis.

Table A.1: Characteristics of high and low exposure firms

	Low exposure	High Exposure	Difference (1)-(2)
	(1)	(2)	(3)
Total Assets (Million Euros)	108.196	76.755	31.440
	(15.515)	(13.243)	(20.375)
Bank Leverage	0.217	0.198	0.019
	(0.009)	(0.009)	(0.013)
$\ln TFPR$	6.342	5.952	0.390
	(0.175)	(0.166)	(0.241)
$\ln TFPQ$	12.694	12.307	0.386
	(0.181)	(0.170)	(0.248)
$\ln P$	1.735	1.679	0.056
	(0.147)	(0.123)	(0.191)
Inventories	0.190	0.191	-0.002
	(0.006)	(0.006)	(0.008)
Demand Elasticity$^{\text{Top 5}}$	0.571	0.592	-0.021
	(0.226)	(0.220)	(0.014)
Demand Elasticity$^{\text{Top 10}}$	0.456	0.478	-0.021
	(0.233)	(0.229)	(0.014)
Z-score	2.019	2.096	-0.077
	(0.047)	(0.048)	(0.068)

Notes: This table compares firm characteristics, measured at the end of fiscal year 2009, across firms borrowing from banks with low holdings (below median) and high holdings (above median) of distressed sovereign bonds. Columns 1 and 2 report means and their standard errors (in parentheses). Column 3 reports the difference and standard errors (in parentheses) of a two-tailed test of equality of the means of the two groups. *** denotes that the mean difference is significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

B Construction of Price Indices

We construct our firm-level price index following the consumer preference-based price index (CUPI) proposed by Redding and Weinstein (2020), and adapted by Eslava and Haltiwanger (2020) in the context of productivity estimation. The original CUPI approach was developed to measure aggregate price dynamics. However, in our case, as in Eslava and Haltiwanger (2020), the objective is to construct a firm-level price index that allows us to capture changes in firms' pricing policies over time and across firms.[34] We start by describing how we construct the changes in the firm-level price index over time. Then, we show how we compute the levels of the price index.

Following Redding and Weinstein (2020), the change in the price index between periods $t-1$ and t for firm j is comprised of three components and is given by:

$$\tilde{P}_{j\tau} := \lambda_{jt}^{J} \lambda_{jt}^{FE} \lambda_{jt}^{RW}.$$

The first term is an equal-weighted geometric-average (a Jevons index) of the prices for all products continuing from period $t-1$ to t, and is given by:

$$\lambda_{jt}^{J} = \frac{\prod_{p \in \Omega_{jt}^{*}} \left(P_{jpt}\right)^{\frac{1}{|\Omega_{jt}^{*}|}}}{\prod_{p \in \Omega_{jt}^{*}} \left(P_{jpt-1}\right)^{\frac{1}{|\Omega_{jt}^{*}|}}},$$

where Ω_{it}^{*} is the set of products continuing from period $t-1$ to t, $|\Omega_{jt}^{*}|$ is the measure (count) of those products, and P_{jpt} is the price of product p for firm j in period t. This term measures the change in the price levels for continuing products.

The second term is given by:

$$\lambda_{jt}^{FE} = \left(\frac{\sum_{p \in \Omega_{jt}^{*}} s_{jpt}}{\sum_{p \in \Omega_{jt}^{*}} s_{jpt-1}} \right)^{\frac{1}{\sigma-1}},$$

where s_{jpt} is the share of product p in firm j's revenues in period t and σ is a parameter measuring the elasticity of substitution between products. This term, attributed to Feenstra (1994), captures changes in the price index due to the entry and exit of products. For example, if the entering products are more attractive than the exiting products (by

[34] While the level of the price index differences out when we examine changes in prices over time, the price levels are relevant for constructing the firm-level quantity measures used in the production function estimation, as discussed in Appendix C.

having lower prices relative to their quality) then the shares of the continuing products should be lower in period t compared to period $t-1$. Thus λ_{jt}^{FE} will be less than one, leading to a decrease in the price index.

The third term, introduced by Redding and Weinstein (2020) is given by:

$$\lambda_{jt}^{RW} = \left(\frac{\prod_{p\in\Omega_{jt}^*} \left(s_{jpt}^*\right)^{\frac{1}{|\Omega_{jt}^*|}}}{\prod_{p\in\Omega_{jt}^*} \left(s_{jpt-1}^*\right)^{\frac{1}{|\Omega_{jt}^*|}}} \right)^{\frac{1}{\sigma-1}},$$

where s_{jpt}^* is the share of product p in firm j's revenues among all products continuing from period $t-1$ to t. This term captures the change in the heterogeneity in shares among common products, driven by heterogeneity in prices. If price heterogeneity increases from $t-1$ to t, then this will be reflected in increased dispersion in shares and a smaller geometric average of the shares, causing λ_{jt}^{RW} to be less than one, leading to a decrease in the price index.

To build the price index in levels, we follow Eslava and Haltiwanger (2020) and first initialize the price index of firm j in the base year as:

$$P_{jB} = P_{base,B} \prod_{\Omega_{jB}} \left(\frac{P_{jpB}}{\bar{P}_{pB}}\right)^{s_{jpB}}, \quad \bar{P}_{pB} = \prod_{j} \left(P_{jpB}\right)^{\frac{1}{\tilde{s}_{jpB}}},$$

where B is the first year in which firm j is in the sample, Ω_{jB} is the set of products produced by firm j in year B, and $\bar{P}_{pB}$ is the geometric average of prices for product p in the base year, with weights $\tilde{s}_{jpB}$ denoting the revenue share of firm j in total revenues for product p in year B. $P_{base,B}$ is an overall base price such that:

$$P_{base,B} = \begin{cases} 1 & \text{if } B \text{ is the first year of the sample} \\ \prod \left(P_{jB-1}\right)^{\frac{1}{\tilde{s}_{jB-1}}} & \text{if } B > \text{first year of the sample} \end{cases}$$

The price index is then built recursively from base year B as:

$$P_{jt} = P_{jB} \prod_{\tau=B+1}^{t} \lambda_{j\tau}^{J} \lambda_{j\tau}^{FE} \lambda_{j\tau}^{RW} = P_{jB} \prod_{\tau=B+1}^{t} \tilde{P}_{j\tau}. \tag{A.1}$$

In the construction of the price index used in our main analysis, we assume an elasticity of substitution across products, σ, equal to 4. In Appendix F we show that our results are not driven by this assumption, reporting the estimated effect of the financial shock on firm-level prices under alternative degrees of elasticity of substitution ($\sigma = 2$ and $\sigma = 8$). Moreover, we also construct two alternative price measures which deliver similarly robust results. The first is a simple revenue-share weighted-average of the product-level prices. The second avoids taking a stance on aggregation across different products, and uses just the change in the price of the firm's main product.

C Production Function Estimation

C.1 Estimation Procedure

Our main production function estimation strategy follows the two-stage estimation routine in Gandhi, Navarro, and Rivers (2020) (GNR, henceforth), augmented to control for differences in output quality (De Loecker et al., 2016), and extended by allowing productivity to evolve according to a controlled Markov process in which firm investments in innovation (R&D and employee training) affect future productivity growth. As discussed in the paper, a key advantage of this approach is that it allows us to treat the production function non-parametrically. Therefore, the resulting productivity estimates are not affected by any parametric assumptions on the production technology. We outline the basic steps of the procedure and refer the reader to GNR for additional details.

C.1.1 Production Functions

We first discuss the quantity production function (in logs) that relates observed output measured in quantities to inputs:

$$q_{jt} = f(k_{jt}, l_{jt}, m_{jt}; \gamma) + \underbrace{\omega_{jt} + \epsilon_{jt}}_{\ln TFPQ_{jt}} \tag{A.2}$$

where k, l, m, are capital, labor, and intermediate inputs (materials, third-party services, and energy consumption) used by the firm to produce (log) quantities q. ω_{jt} is a persistent productivity shock that is observable by the firm when it makes production decisions, and unobserved by the econometrician. ϵ_{jt} represents non-persistent shocks that are not observable (or predictable) by firms before making their input decisions at t. Physical productivity, TFPQ, is defined as the sum of these two shocks and therefore can be formed as:

$$\ln TFPQ_{jt} = q_{jt} - f\left(k_{jt}, l_{jt}, m_{jt}; \gamma\right).$$

As discussed in the main text, from this measure we can construct our first measure of revenue productivity, which we denote $\mathrm{TFPR}^{\mathrm{Q}}$ as $\ln TFPR^{Q}_{jt} = \ln TFPQ_{jt} + \ln P_{jt}$.

Our second measure of revenue productivity, $\mathrm{TFPR}^{\mathrm{R}}$, is computed as the residual of a revenue production function relating output, measured in revenues, to inputs:

$$r_{jt} = f(k_{jt}, l_{jt}, m_{jt}; \tilde{\gamma}) + \underbrace{\tilde{\omega}_{jt} + \tilde{\epsilon}_{jt}}_{\ln TFPR^{R}_{jt}}, \tag{A.3}$$

where we use $\tilde{\gamma}$, $\tilde{\omega}$, and $\tilde{\epsilon}$ to distinguish these objects from those of the quantity-based production function.

C.1.2 Estimation Routine

We assume that productivity evolves following a controlled first-order Markov process. Specifically, as in Ericson and Pakes (1995) and Doraszelski and Jaumandreu (2013), the distribution of productivity in period t is allowed to depend on past expenditures on innovation as well as past realizations of productivity:

$$P_{\omega}\left(\omega_{jt} \mid \mathcal{I}_{jt-1}\right) = P_{\omega}\left(\omega_{jt} \mid \omega_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2}\right)$$

where $\mathcal{I}_{jt}$ denotes the firm's information set in period t and the vector $\boldsymbol{Z}_j$ includes firm j's investment rate in R&D, a dummy indicating any R&D expense, and training expenses per employee. This implies that we can write $\omega_{jt} = h\left(\omega_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2}\right) + \xi_{jt}$, where $h\left(\omega_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2}\right) = \mathbb{E}\left[\omega_{jt} \mid \omega_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2}\right]$ and ξ_{jt} is an unanticipated productivity "innovation" such that $\mathbb{E}\left[\xi_{jt} \mid \mathcal{I}_{jt-1}\right] = 0$. ϵ_{jt} is an unanticipated shock to output that is assumed to be independent of the firm's information set in period t, and thus $\mathbb{E}[\epsilon_{jt}|\mathcal{I}_{jt}] = \mathbb{E}[\epsilon_{jt}] = 0$. Capital and labor are assumed to pre-determined, i.e., k_{jt} and l_{jt} are assumed to be in the firm's information set in period t. Intermediate inputs as flexibly chosen in period t.

The estimation routine consists of two steps. We outline these steps following the non-parametric setup in GNR. Step 1 non-parametrically identifies the output elasticities of intermediate inputs using the link between the production function and the first-order condition for flexible inputs. Step 2 uses the estimates of Step 1 to recover the part of the production function that does not depend on intermediate inputs, in particular, the output elasticities with respect to capital and labor.

Step 1. *Recovering the elasticity with respect to intermediate inputs* (θ_{it}^{M}).

The first step of the estimation strategy in GNR is based on a transformation of the firm's first-order condition for intermediate inputs, which relates observed input shares for intermediate inputs to the elasticity of output for intermediate inputs. Specifically, the first step shows that the output elasticity of intermediate inputs, $\frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt})$, can be recovered by regressing the shares of intermediate inputs on input levels:

$$s_{jt} = \ln\left(\frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt})\right) - \epsilon_{jt} \tag{A.4}$$

where $s_{jt} \equiv \frac{P_t^M M_{jt}}{R_{jt}}$ are the intermediate input shares, and P_t^M is the price of intermediates.[35]

GNR proposes a sieve estimator for equation (A.4) that we also employ:

$$\theta_{jt}^{M}\left(k_{jt}, l_{jt}, m_{jt}\right) = \sum_{r_k + r_l + r_m \le r} \gamma_{r_k, r_l, r_m} k_{jt}^{r_k} l_{jt}^{r_l} m_{jt}^{r_m},$$

where $\theta_{jt}^{M}\left(k_{jt}, l_{jt}, m_{jt}\right) \equiv \frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt})$ is the output elasticity of intermediate inputs and we set $r = 2$. We estimate the γ's by solving the following minimization problem by non-linear least squares:

$$\min_{\gamma} \sum_{j,t} \left\{ s_{jt} - \ln\left(\sum_{r_k, r_l, r_m} \gamma_{r_k, r_l, r_m} k_{jt}^{r_k} l_{jt}^{r_l} m_{jt}^{r_m}\right)\right\}^2 .$$

We recover an estimate of $\hat{\epsilon}_{jt}$ using the residuals and an estimate of the output elasticity of intermediate inputs as:

$$\hat{\theta}_{jt}^{M} = \exp\left\{\sum_{r_k, r_l, r_m} \hat{\gamma}_{r_k, r_l, r_m} k_{jt}^{r_k} l_{jt}^{r_l} m_{jt}^{r_m}\right\}.$$

Step 2. *Recovering the elasticities with respect to capital and labor* (θ_{jt}^{K} and θ_{jt}^{L}).

The second step of the estimation procedure recognizes that the first stage defines a partial differential equation in the production function that can be used to recover the remainder of the production function. By the fundamental theorem of calculus:

[35] GNR also includes in equation (A.4) a constant term $\ln(\mathcal{E}) = \ln\left(E\left[e^{\epsilon_{jt}}\right]\right)$. For simplicity and since Gandhi, Navarro, and Rivers (2020) notes that this term is close to zero in practice, we abstract away from this.

$$\int \frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt}) dm_{jt} = f(k_{jt}, l_{jt}, m_{jt}) + C(k_{jt}, l_{jt}), \tag{A.5}$$

where $\frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt})$ is recovered in Step 1 and $C(k_{jt}, l_{jt})$ is a constant of integration that is a function only of capital and labor.

Let y_{jt} denote the output of the firm (either in quantities or revenues); we have that $y_{jt} = f\left(k_{jt}, l_{jt}, m_{jt}\right) + \omega_{jt} + \epsilon_{jt}$. Substituting this in equation A.5 we have that:

$$\mathcal{Y}_{jt} \equiv y_{jt} - \epsilon_{jt} - \int \frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt}) dm_{jt} = \omega_{jt} - C(k_{jt}, l_{jt}) \tag{A.6}$$

where $\mathcal{Y}_{jt}$ is an "observable term" that can be recovered from the estimates in Step 1.

In order to compute an estimate of the integral $\int \frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt}) dm_{jt}$, GNR shows that given the sieve approximation of $\frac{\partial}{\partial m_{jt}} f(k_{jt}, l_{jt}, m_{jt})$, its integral with respect to m_{jt} has an analytical closed-form solution, which they denote as $\mathcal{D}_M(k_{jt}, l_{jt}, m_{jt})$.

Exploiting the Markovian property of ω_{jt}, equation (A.6) can be re-written as:

$$\mathcal{Y}_{jt} = \underbrace{h\left(\mathcal{Y}_{jt-1} + C(k_{jt-1}, l_{jt-1})\right)}_{h(\omega_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2})} + C(k_{jt}, l_{jt}) + \xi_{jt}.$$

Using sieves for $C(k_{jt}, l_{jt})$ and $h\left(\omega_{jt-1}, \boldsymbol{Z}_{jt-1}, \boldsymbol{Z}_{jt-2}\right)$, we have:

$$C(k_{jt}, l_{jt}) = \sum_{0<\tau_k+\tau_l\leq\tau} \gamma_{\tau_k,\tau_l} k_{jt}^{\tau_k} l_{jt}^{\tau_l} \tag{A.7}$$

$$h(\omega_{jt-1}) = \sum_{0<a\leq A} \psi_a \tilde{\omega}_{jt-1}^a + \sum_{0<b_1\leq B_1} \varphi_{b_1} \boldsymbol{Z}_{jt-1}^{b_1} + \sum_{0<b_2\leq B_2} \varphi_{b_2} \boldsymbol{Z}_{jt-2}^{b_2}. \tag{A.8}$$

Combining equations (A.7) and (A.8), we construct the following recursive estimation equation:

$$\begin{aligned} \mathcal{Y}_{jt}(\psi, \gamma) \quad = \quad & -C(k_{jt}, l_{jt}; \gamma) + \sum_{0<a\leq A} \psi_a \left(\mathcal{Y}_{jt-1}(\psi, \gamma) + C(k_{jt-1}, l_{jt-1}; \gamma)\right)^a \\ & + \sum_{0<b_1\leq B_1} \varphi_{b_1} \boldsymbol{Z}_{jt-1}^{b_1} + \sum_{0<b_2\leq B_2} \varphi_{b_2} \boldsymbol{Z}_{jt-2}^{b_2} + \xi_{jt} \end{aligned} \tag{A.9}$$

and identify the vector of coefficients (ψ, φ, γ) from the following moment conditions:

$$
\begin{aligned}
\mathbb{E}[\xi_{jt} \cdot k_{jt}^{\tau_k} l_{jt}^{\tau_l}] &= 0 \\
\mathbb{E}[\xi_{jt} \cdot \mathcal{Y}_{jt-1}^{a}] &= 0. \\
\mathbb{E}[\xi_{jt} \cdot \boldsymbol{Z}_{jt-1}^{b_1}] &= 0. \\
\mathbb{E}[\xi_{jt} \cdot \boldsymbol{Z}_{jt-2}^{b_2}] &= 0.
\end{aligned}
$$

Given estimates of these coefficients, we can construct non-parametric estimates of the output elasticities of capital and labor (θ_{jt}^{K} and θ_{jt}^{L}):

$$
\hat{\theta}_{jt}^{K} = \frac{\partial \hat{\mathcal{D}}_M(k_{jt}, l_{jt}, m_{jt})}{\partial k_{jt}} + \frac{\partial \hat{C}(k_{jt}, l_{jt})}{\partial k_{jt}}
$$

$$
\hat{\theta}_{jt}^{L} = \frac{\partial \hat{\mathcal{D}}_M(k_{jt}, l_{jt}, m_{jt})}{\partial l_{jt}} + \frac{\partial \hat{C}(k_{jt}, l_{jt})}{\partial l_{jt}}
$$

Controlling for Input Price Bias in Quantity Production Functions. The final component of our estimation procedure concerns the quantity-based specification. In a typical production function estimation, data on physical quantities of output and inputs are often not available and instead are measured as values (revenues for output and expenditures for inputs) that are deflated by common aggregate (often industry-level) deflators. Previous work has shown that this can lead to biased estimates of the production function and productivity (Katayama, Lu, and Tybout, 2009). Under some conditions, these biases cancel out (see De Loecker and Goldberg, 2014). However, when output is measured in quantities, the biases no longer cancel out. To deal with this, we follow the approach in De Loecker et al. (2016), which suggests using a control function of (output) prices and market shares to correct for the bias.

In practice, for the quantity-based production function estimation, we augment the production function with a control function in prices and market shares. That is, we replace $C(k_{jt}, l_{jt})$ with $C(k_{jt}, l_{jt}) + cf\left(P_{jt}, ms_{jt}\right)$ in equation (A.9):

$$
\begin{aligned}
\mathcal{Y}_{jt}(\psi, \gamma) = \quad & -C(k_{jt}, l_{jt}; \gamma) - cf(P_{jt}, ms_{jt}; \phi) \\
& + \textstyle\sum_{0<a\leq A} \psi_a \left(\mathcal{Y}_{jt-1}(\psi, \gamma) + C(k_{jt-1}, l_{jt-1}; \gamma) + cf(P_{jt-1}, ms_{jt-1}; \phi)\right)^a \\
& + \textstyle\sum_{0<b_1\leq B_1} \varphi_{b_1} \boldsymbol{Z}_{jt-1}^{b_1} + \sum_{0<b_2\leq B_2} \varphi_{b_2} \boldsymbol{Z}_{jt-2}^{b_2} + \xi_{jt}
\end{aligned}
\tag{A.10}
$$

where we also approximate $cf(\cdot)$ with a sieve in price and market shares. Accordingly, we add moments interacting ξ_{jt} and the terms of the sieve approximation to estimate the parameters (ϕ) of the sieve for $cf(\cdot)$. The remaining steps of the estimation procedure are unchanged.

C.2 Estimation Results

We perform the production function estimation separately for each 2-digit industry for both the quantity-based and revenue-based specifications (equations (A.2) and (A.3)). In Table A.2, we report the average elasticity estimates for each industry under our baseline specification with a non-parametric specification of the production technology $f(\cdot)$. For both the quantity and revenue versions, the elasticity estimates are sensible, highlighting roughly constant returns to scale, on average, across industries. Elasticity estimates imposing a Cobb-Douglas specification (using both the GNR method and using the index function approach) are largely similar and are available upon request. Appendix F shows that our results are robust to using the productivity estimates from these alternatives.

Table A.2: Production function estimates

	Output Elasticities					
	Quantity-Based			Revenue-Based		
Industry Code (NACE Rev. 1.1)	θ^L	θ^K	θ^M	θ^L	θ^K	θ^M
15	0.179	0.060	0.757	0.189	0.057	0.757
17	0.295	0.029	0.686	0.292	0.034	0.686
18	0.239	0.047	0.741	0.243	0.048	0.741
20	0.184	0.114	0.725	0.222	0.092	0.725
21	0.201	0.090	0.687	0.207	0.082	0.687
22	0.206	0.019	0.732	0.224	0.027	0.732
24	0.230	0.074	0.723	0.234	0.071	0.723
25	0.235	0.071	0.704	0.228	0.065	0.704
26	0.286	0.089	0.652	0.316	0.064	0.652
27	0.155	0.125	0.745	0.203	0.059	0.745
28	0.260	0.082	0.654	0.289	0.063	0.654
29	0.302	0.056	0.673	0.307	0.038	0.673
31	0.288	0.047	0.665	0.306	0.043	0.665
32	0.323	0.078	0.573	0.288	0.074	0.573
33	0.227	0.011	0.693	0.231	0.016	0.693
36	0.217	0.067	0.713	0.237	0.046	0.713

Notes: This table reports the within industry average production function elasticities estimated using the approach of Gandhi, Navarro, and Rivers (2020), as described above. The first three columns report the estimates obtained from a quantity production function estimation. The last three columns report the estimates obtained from a revenue production function estimation.

D Theoretical framework

In this section, we present a theoretical framework that illustrates why firms have incentives to implement more aggressive pricing policies in response to an unexpected contraction of credit supply. Our theoretical framework builds upon and extends the framework in Hendel (1996), highlighting that the incentives and ability to respond to the shock by adjusting prices depends on product market conditions and the availability of inventories.

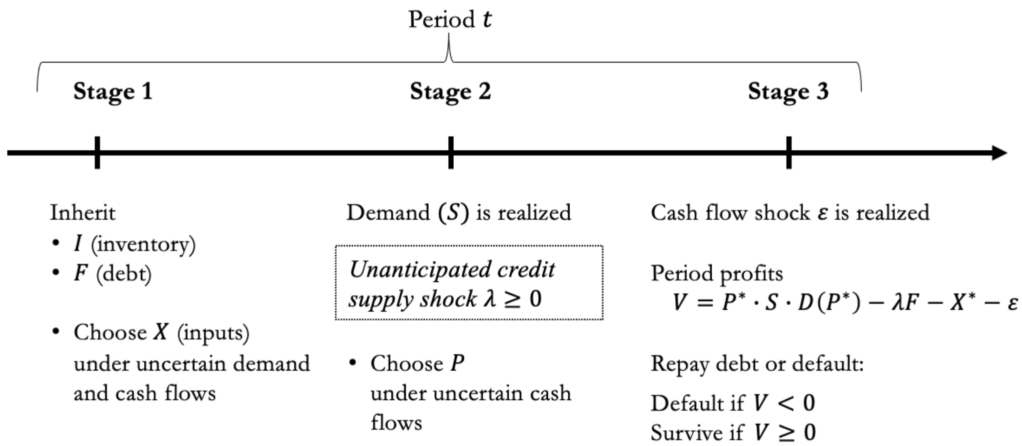
Production decisions. Consider a firm sequentially deciding production and pricing policies as uncertainty gradually resolves. Figure A.1 presents the timing of firm decisions.

The firm enters each period with a given stock of inventories $I \geq 0$ from previous periods and an amount of debt $F > 0$ that is due at the end of the period. Given I and F, the firm makes production decisions, deciding how many units of input, $X > 0$, to acquire in order to produce $Q = f(X)$ units of output.[36] X is supplied inelastically at a unit-cost of one, which is paid by the firm at the end of the period after cash flows are collected. Production decisions take place under uncertainty. The first source of uncertainty stems from demand uncertainty. In particular, the firm faces an elastic demand for their products, $D(P,S) = D(P,E) \cdot S$ (with $D_P(P,E) < 0$), where $S \geq 0$ denotes a demand shifter that is realized after X has been committed and $E > 1$ denotes the elasticity of demand. Because production decisions have already taken place when consumer demand is realized, the firm uses inventories to deal with fluctuations in demand. Inventories are shed in high demand states and carried over to the following period together with unsold output $(I + Q - D(P,E) \cdot S)$ in low demand states. We assume that a fraction $\delta \in (0,1]$ of the output carried over is sunk. The parameter δ captures the opportunity cost of using inventories today versus using them in the future; it can be interpreted as the degree of durability of inventories. The second source of uncertainty stems from unforeseen cash flow shocks, ϵ, which are realized at the end of the period before input and debt payments are due. We denote the cumulative distribution function of ϵ as Φ.

The cost of financial distress. The uncertainty regarding future cash flows exposes firms to the possibility of default. If end-of-period cash-flows are sufficient to repay all stakeholders, the firm survives with continuation value $\overline{\pi} > 0$. Otherwise the firm enters

[36] One can think of X as a composite input (e.g., "labor-plus-capital-plus-intermediates").

Figure A.1: Timing of firms' decisions



Notes: This figure presents the timing of firms' production and and pricing decisions as uncertainty regarding demand conditions and future cash flows is resolved. In stage 2, we introduce the possibility of an unanticipated credit supply shock ($\lambda \geq 0$) which generates additional liquidity needs and, *ceteris paribus*, increases the likelihood of financial distress in stage 3.

---

a default state, with default continuation value $\underline{\pi} < \overline{\pi}$. The difference in continuation values ($\Delta\pi = \overline{\pi} - \underline{\pi}$) captures the costs of financial distress, such as the costs associated to bankruptcy litigation or asset fire-sales.

Pricing policies. Firms decide their pricing policies, P, after demand conditions are revealed but before observing the realization of the cash flow shock. In normal credit market conditions, firms count on entirely rolling over their debt obligations. In this scenario, the end-of-period cash flows are given by $P \cdot \min\{I + Q, D(P, E) \cdot S\} - X + \epsilon$. When financial markets are in distress, firms need to cope with an *unanticipated* credit supply shock, which implies that a fraction of their debt cannot be rolled over. Letting $\lambda \in (0, 1]$ denote the fraction of current debt that has to be paid out at the end-of-period, the cash flows of a firm coping with an unexpected tightening of credit supply are thus given by $P \cdot \min\{I + Q, D(P, E) \cdot S\} - \lambda F - X + \epsilon$.

Firms adjust their pricing policies in order to best respond to the cash flow uncertainty and, when credit markets are in distress, to the unexpected tightening of financial conditions, subject to the constraint that quantity demanded does not exceed total available supply: $D(P, E) \cdot S \leq I + Q$. The optimal pricing policy P^* solves the following problem:

$$\begin{aligned} \max_P \ \mathcal{L} = \ & P \cdot D(P,E) \cdot S - \lambda F - X + \delta(Q + I - D(P,E) \cdot S) \\ & + \Delta\pi \cdot (1 - \Phi(-(P \cdot D(P,E) \cdot S - \lambda F - X))) + \underline{\pi} + \varsigma(I + Q - D(P,E) \cdot S). \end{aligned} \tag{A.11}$$

The multiplier $\varsigma \geq 0$ represents the shadow value of inventories, which is zero for any interior solution in which the firm's pricing policies are not constrained by production capacity. When $D(P^*, E) \cdot S < Q + I$, the problem has an interior solution characterized by:

$$\begin{aligned} & [P^* - \delta]\, D_P(P^*, E) \cdot S + D(P^*, E) \cdot S \\ & + \Delta\pi \cdot \phi(-(P^* \cdot D(P^*, E) \cdot S - \lambda F - X))\, (P^* \cdot D_P(P^*, E) \cdot S + D(P^*, E) \cdot S) \quad = 0 \end{aligned} \tag{A.12}$$

The first line in equation (A.12) is a reformulation of a standard optimal pricing condition under downward-sloping demand. That is, absent risk/liquidity considerations, firms act as static profit maximizers, setting $P = \frac{E}{(1+E)}\delta$, where the cost of depleting inventories plays the role of the marginal cost of production since other production costs are sunk when the unexpected credit shock hits the firm. This price represents the upper bound of the (optimal) pricing function, which we denote as $\bar{P}$.[37] The second term in equation (A.12) represents the increase in the probability of surviving due to an additional dollar of revenue ($\phi(-(P \cdot D(P,E) \cdot S - \lambda F - X))$) multiplied by the product of marginal revenue ($P \cdot D_P(P,E) \cdot S + D(P,E) \cdot S$) and the future benefit of not defaulting ($\Delta\pi$).

At the statically optimal price, $\bar{P}$, the first line in equation (A.12) is equal to zero, as this is the price that balances the static incentives. The second line is negative, which generates an incentive for firms to lower prices, and thus $P^* < \bar{P}$.[38] The intuition for this result is straightforward. As discussed in Hendel (1996), the cash-flow uncertainty and the cost of financial distress ($\Delta\pi > 0$) make liquidity valuable, and firms therefore maximize a combination of current profits and revenues. This is the key force driving the firms' pricing decisions in response to financial shocks. Coping with future cash flow uncertainty, firms choose to price below the static profit-maximizing price, $P^* < \bar{P}$. This choice sacrifices current profits but allows the firm to build a liquidity buffer that can be

[37] The lower bound, $\underline{P}$, is the minimum price a firm can set without violating the capacity constraint on output sold, where $D\left(\underline{P}, E\right) \cdot S = I + Q$.

[38] The terms $\Delta\pi$ and $\phi(\cdot)$ are positive, but the last term, which is the marginal revenue with respect to price, is negative when evaluated at the statically optimal price, $\bar{P}$.

used to cope with adverse cash flow shocks.

An unanticipated tightening of credit supply conditions ($\lambda > 0$) increases the likelihood of future financial distress and thereby strengthens firms' revenue maximizing behavior and the incentives to price more aggressively. As a result, larger shocks to credit supply generate larger reductions in price: $\frac{\partial P^*}{\partial \lambda} < 0$.[39]

Heterogeneous pricing response. The model offers theoretical predictions regarding differences across firms in their incentive and ability to respond to a credit supply shock by implementing more aggressive pricing policies.

A first prediction relates the pricing response to product market characteristics. Consider two firms facing different demand elasticities, denoted E^{Low} and E^{High}. As discussed above, when faced with an unanticipated tightening of credit supply ($\lambda > 0$), both firms have an incentive to reduce prices. However, the more elastic the demand, the greater are the revenues that can be collected by lowering prices, and therefore the greater the incentives to lower prices in response to a credit shock. This can be seen from first-order condition in equation (A.12). In the second line, the marginal revenue with respect to price is larger—in absolute value—for firms facing more elastic demand. Moreover, the demand elasticity also affects the change in the probability of financial distress $\phi(\cdot)$. *Ceteris paribus,* a high demand elasticity implies lower profits. Assuming that the density ϕ is monotone in the tails, a lower value of profits, which implies a larger value for the index in $\phi(\cdot)$, implies a larger value of $\phi(\cdot)$. Together this implies that, for any given λ shock, the second line in equation (A.12) is more negative for high E firms, and thus are predicted to have a stronger price response to financial shocks. That is, $\left|\frac{\partial P^*}{\partial \lambda}|_{E^{Low}}\right| < \left|\frac{\partial P^*}{\partial \lambda}|_{E^{High}}\right|$.

A second prediction relates the pricing response to the availability of inventories. When inventories are sufficiently high, firms can fully respond to credit shocks by reducing prices. However, when inventories are not sufficiently high, the quantity demanded can exceed the total available supply ($I + Q$), and thus the optimal price is a corner solution to the problem in equation (A.11). In this case, the shadow value of

[39]For highly leveraged firms (high F) facing a significant credit supply contraction (high λ), the increase in the probability of financial distress due to the shock may be so substantial that the expected benefits of reducing prices to minimize this probability is lower than the foregone current profits. Thus, for firms close to financial distress (i.e., high values of λF), the optimal pricing response is increasing rather than decreasing output prices.

inventories, ς, is positive, and this term pushes the optimal price up to the point where quantity demanded equals total available supply: $D(P, E) \cdot S = I + Q$. As a result, because a lower inventory stock leaves the firm little room to promptly ramp up goods supply, *ceteris paribus,* a firm with lower inventories has a lower ability to respond to a credit supply shock by reducing prices. That is, $\left|\frac{\partial P^*}{\partial \lambda}|_{I^{Low}}\right| \leq \left|\frac{\partial P^*}{\partial \lambda}|_{I^{High}}\right|$.

E The pass-through of the sovereign shock to credit supply

E.1 The burst of the European sovereign debt crisis.

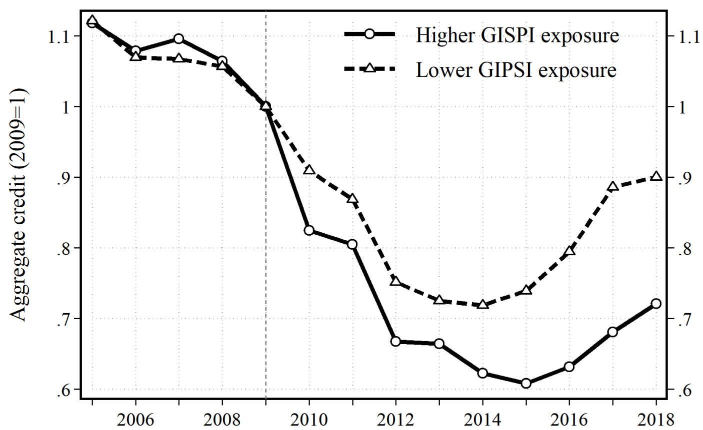
After the parliamentary elections held in Greece in October 2009, the newly elected government acknowledged significant budget misreporting in previous years and a larger-than-expected fiscal deficit, which forced the Greek government to request, on April 23, 2010, an EU/IMF bailout package to cover its financial needs for the remainder of the year. In response to these events, international rating agencies downgraded Greece's sovereign debt rating to "junk bond" and the yields on Greek government bonds rose sharply, effectively barring the country's access to capital markets (Lane, 2012).

Shortly after the events in Greece, investors became concerned with the solvency and liquidity of the public debt issued by other peripheral European countries, starting with Ireland and Portugal, and soon after Spain and Italy (Angelini, Grande, and Panetta, 2014). Figure 1 in the paper displays the spread between the yield to maturity of 10 year bonds issued by GIPSI countries (Greece, Italy, Portugal, Spain, and Ireland) and the yield to maturity of the German 10 year bonds. The yield spread with Germany, which had been low and relatively stable for most Euro-zone countries since the introduction of the euro, significantly increased following news from Greece and the subsequent bailout at the end of the first quarter of 2010.

Investigating the channels of transmission of the financial shock to bank lending activity, Bottero, Lenzu, and Mezzanotti (2020) documents that the sovereign shock affected banks' lending because it unexpectedly increased the riskiness of bank assets, forcing financial intermediaries with low capital buffers to adjust the riskiness of their assets, and also impaired the ability to pledge these securities as collateral in interbank transactions, which is a crucial funding source for many banks.

The balance sheet shock had important credit supply implications. Figure A.2 plots the aggregate credit supplied to the firms in our dataset by financial intermediaries with above versus below median exposure to the sovereign crisis. It shows that, right after the burst of the crisis, the amount of credit provided by the two groups of banks started diverging relative to the pre-shock period.

Figure A.2: Aggregate credit



Notes: This figure displays the time-series evolution of the aggregate credit supply provided by banks with above versus below median exposure to the sovereign crisis in the last quarter before the Greek bailout request (2010:Q1). Exposure to the sovereign crisis is based on residual holdings of GIPSI debt, as described in the main text. Both series are normalized by their 2009 level.

E.2 The effect of banks' sovereign holdings on firm-level credit supply.

Table A.3 reports the estimated cumulative effect of the bank balance sheet shock on the firm-level growth rate of bank credit (column 1) and the firm-level change in financing costs (column 2). Figure 2 in the paper graphs the coefficients and associated confidence intervals. In addition to the pre-trend check discussed in the main body of the paper, we perform a series of robustness analyses to test the validity of our identification strategy, which we discuss below.

Within-firm estimator. We present additional analysis that supports the identification assumption that the drop in credit observed in the data is explained by a sudden tightening

Table A.3: Exposure to the sovereign shock and credit market outcomes

Δ_τCredit (1)				$\Delta_\tau fc$ (2)			
Pre-shock		Post-shock		Pre-shock		Post-shock	
$\hat{\beta}_{-3}$	0.015	$\hat{\beta}_1$	-0.119***	$\hat{\beta}_{-3}$	-0.009	$\hat{\beta}_1$	0.007
	(0.056)		(0.037)		(0.006)		(0.006)
$\hat{\beta}_{-2}$	0.038	$\hat{\beta}_2$	-0.058	$\hat{\beta}_{-2}$	-0.002	$\hat{\beta}_2$	0.016
	(0.042)		(0.041)		(0.008)		(0.010)
$\hat{\beta}_{-1}$	0.042	$\hat{\beta}_3$	-0.169***	$\hat{\beta}_{-1}$	0.002	$\hat{\beta}_3$	0.035**
	(0.034)		0.059)		(0.008)		(0.015)
		$\hat{\beta}_4$	-0.145*			$\hat{\beta}_4$	0.023**
			(0.069)				(0.009)
		$\hat{\beta}_5$	-0.024			$\hat{\beta}_5$	0.025**
			(0.063)				(0.010)
		$\hat{\beta}_6$	0.022			$\hat{\beta}_6$	-0.005
			(0.066)				(0.009)
		$\hat{\beta}_7$	0.002			$\hat{\beta}_7$	-0.001
			(0.105)				(0.007)

Notes: This table accompanies Figure 2. It reports the estimates of the effect of the credit supply shock on the cumulative growth rate of firm-level credit and the change in the average financing costs using model (5). All regressions include bank-level controls, firm-level controls, industry fixed effects, and region fixed effects. Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

of credit *supply* rather than driven by demand-side factors. In particular, we address the potential concern that the coefficients are picking up a shift in firms' credit demand or a change in borrower's credit worthiness that takes place at the same time as the credit shock. To do so, we leverage the micro-data containing information on individual firm-bank relationships. Because the vast majority of the firms engage in multiple lending relationships at the same time, we can augment model (5) with firm fixed effects (i_j) and test whether banks with larger GIPSI holdings reduced their credit supply to the *same firm* relative to banks with lower holdings. By exploiting variation across lenders to the same firm, this within-firm estimator allows us to control for changes in unobservable firm-specific factors, such as a simultaneous contraction of credit demand or a worsening of firms' credit worthiness.

Specifically, we estimate the following model at different horizons indexed by τ:

$$\Delta_\tau \text{Credit}_{jb} = \beta_\tau \cdot \text{GIPSI Sovereigns}_{jb} + \Gamma^{'}_{K,\tau}\mathbf{K}_{jb} + \Gamma^{'}_{X,\tau}\mathbf{X}_{jb} + i_{j,\tau} + u_{jb\tau}, \tag{A.13}$$

where now the left-hand side is the cumulative growth rate of credit to firm j that is provided by bank b specifically, $\Delta_\tau\text{Credit}_{jb}$, as opposed to the total credit summed across all banks.[40] In this case, the right-hand side variable of interest is the interaction between bank b's holdings of sovereign securities issued by GIPSI countries scaled by bank b's risk-weighted assets before the Greek bailout (GIPSI Sovereigns_{jb}). As we did in our main firm-level specification in Section 3 (model 5), we condition on a set of bank-level controls ($\mathbf{K}_{jb}$), which are now measured at the individual bank level, as well as two relationship-level controls ($\mathbf{X}_{jb}$)—the length of the lending relationship between firm j and lender b and the share of credit provided by lender b in firm j total credit—all measured before the the burst of the crisis. Finally, note that the industry and region fixed effects in model (5) are subsumed here by the firm fixed effects. As in our firm-level specification, we de-mean and scale the variable of interest (GIPSI Sovereigns_{jb}) by its standard deviation so that the coefficients β_τ in (A.13) capture the effect of a one standard deviation difference in the exposure to the credit shock on the $\tau-$year cumulative growth rate of credit to firm j from lender b.

Table A.4, column 1, presents the estimation results. The estimates show that among

[40]In the construction of credit growth rates at the relationship level, we account for banks M&A by adopting the standard correction that identifies bank acquisitions over pairs of consecutive years and treats the acquired and acquiring bank as a single entity over that span (Bernanke, Lown, and Friedman, 1991).

Table A.4: Response of growth rate of credit to negative credit supply shocks: Within-firm estimation

	Total Growth ($\Delta_\tau \text{Credit}_{jb}$)		Extensive Margin ($\text{Cut}_{jb\tau}$)		Intensive Margin ($\Delta_\tau \ln\text{Credit}_{jb}$)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}_1$	-0.245***	-0.271***	0.088***	0.086***	-0.080***	-0.101***
	(0.036)	(0.038)	(0.023)	(0.012)	(0.020)	(0.027)
	0.494	*0.080*	*0.464*	*0.052*	*0.455*	*0.051*
$\hat{\beta}_2$	-0.195***	-0.183***	0.060**	0.051**	-0.145***	-0.122***
	(0.043)	(0.060)	(0.026)	(0.023)	(0.059)	(0.029)
	0.489	*0.049*	*0.497*	*0.052*	*0.472*	*0.030*
$\hat{\beta}_3$	-0.177*	-0.175***	-0.005	0.012	-0.412***	-0.317***
	(0.086)	(0.078)	(0.031)	(0.032)	(0.117)	(0.059)
	0.526	*0.024*	*0.489*	*0.045*	*0.555*	*0.036*
$\hat{\beta}_4$	-0.146*	-0.212**	-0.006	0.005	-0.504***	-0.564***
	(0.083)	(0.069)	(0.032)	(0.044)	(0.083)	(0.070)
	0.530	*0.030*	*0.546*	*0.049*	*0.554*	*0.046*
$\hat{\beta}_5$	-0.199*	-0.250***	0.014	0.044	-0.572**	-0.565***
	(0.105)	(0.070)	(0.046)	(0.044)	(0.146)	(0.095)
	0.532	*0.036*	*0.540*	*0.064*	*0.606*	*0.049*
$\hat{\beta}_6$	-0.263*	-0.304***	0.032	0.040	-0.652***	-0.738***
	(0.124)	(0.090)	(0.051)	(0.050)	(0.149)	(0.086)
	0.520	*0.041*	*0.532*	*0.077*	*0.576*	*0.052*
$\hat{\beta}_7$	-0.339***	-0.391***	0.035	0.073	-0.791***	-0.930***
	(0.109)	(0.074)	(0.042)	(0.036)	(0.122)	(0.065)
	0.524	*0.052*	*0.526*	*0.079*	*0.564*	*0.075*
Firm FE	Y	N	Y	N	Y	N

Notes: This table reports estimates of the effect of the credit supply shock on credit growth at the firm-bank relationship-level using model (A.13). We report estimates for overall credit growth as well as the extensive and intensive margin separately, both with and without firm fixed effects. All regressions include bank-level controls and relationship-level controls. Standard errors are clustered at the lender-level and are reported in parentheses. R^2 are reported in italics. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

banks lending to the *same* firm, those that were more exposed to the shock (i.e., had larger holdings of GISPI sovereigns) decreased their lending to that firm relative to less exposed banks, providing strong evidence that the credit contraction was supply-driven. In column 2, we repeat the relationship-level regression, but omitting the firm fixed effects. Importantly, while the estimated coefficients are largely unaffected by whether we include firm-fixed effects, the R^2 of the regressions increase significantly (by about an order of magnitude) when fixed effects are included. In the spirit of Oster (2019), this observation demonstrates that while unobserved firm-specific factors (e.g., changes in credit demand) are important for explaining the overall variation in bank lending to firms, that variation is not correlated with exposure to the sovereign shock.

Table A.4 also highlights that the contraction in credit supply driven by the balance sheet shock is evident both along the intensive and extensive margins. For the extensive margin, we define the variable $\text{Cut}_{jb\tau}$ as an indicator variable for whether a lending relationship that existed between firm j and bank b before the sovereign crisis is still in place τ-years after the shock, with a 1 indicating the relationship is no longer in place. We also calculate the percentage change in credit balances between firm j and bank b for relationships that are in place both before the shock and τ-years after the shock ($\Delta_\tau \text{lnCredit}_{jb}$). Columns 3 and 4 show that banks more exposed to the shock are more likely to break existing lending relationships. Columns 5 and 6 show that banks also reduce their credit supply in surviving relationships. As was the case for the overall credit results, including firm fixed effects increases the R^2 but has little effect on the coefficients.

Finally, we note that the contraction in credit at the firm-bank level persists throughout out sample period, whereas the contraction in credit at the firm level (Figure 2 and Table A.3) was transitory. Together, these results suggest that over time firms were gradually able to compensate for the contraction in credit supply by their most exposed pre-shock lenders by establishing new lending relationships with other financial intermediaries.

F Robustness: Effect of the Shock on Productivity and Prices

Alternative productivity measures. In the baseline regressions reported in the paper, we estimate the measures of firm-level productivity as residuals from revenue or quantity production functions (see Section 2.2 in the paper and Appendix C). In this Appendix, we test the robustness of our results regarding the effect of financial shocks on productivity to alternative measures of productivity, which are reported in Table A.5.

In our main estimates, we model firms' production technologies non-parametrically. In columns 1 and 2, we repeat the revenue and quantity production function estimation assuming a less flexible but more traditional Cobb-Douglas functional form. In columns 3 and 4, instead of estimating the production function parameters, we calibrate input elasticities to the average revenue shares within each industry (index function approach). Overall, the estimates displayed in Table A.5 are comparable to the ones obtained by our flexible production function estimation approach, although less precisely estimated.

Alternative price measures. As explained in the paper, when constructing a firm-level price index, one needs to take a stance on how to aggregate the prices across the heterogeneous products produced by a firm. We did so following the consumer preference-based price index (CUPI) approach proposed by Redding and Weinstein (2020). Here we show that the estimated contraction and subsequent rebound of output prices following a negative credit supply shock is also evident when one uses alternative measures of firm-level prices.

We first show that the estimated treatment effect of the credit supply shock on prices is qualitatively similar under different values of σ, the consumer elasticity of substitution across goods. Our baseline analysis assumes a value of $\sigma = 4$. Columns 1 and 2 in Table A.6 report the estimated the treatment effects assuming two alternative values, $\sigma = 2$ and $\sigma = 8$, that are at the tails of the distribution of the estimates of the elasticity of substitution commonly found in the literature (Broda and Weinstein, 2006).

Second, we take a simpler approach in the aggregation of prices of different products. We compute a firm-level price index, P_{jt}^{Rev}, as the revenue-share weighted average of 8-digit product prices. The estimation results, reported in column 3, once again

Table A.5: Response of productivity to negative credit supply shocks
Alternative measures of productivity

	Cobb-Douglas		Index Function	
	$\Delta \ln TFPR$	$\Delta \ln TFPQ$	$\Delta \ln TFPR$	$\Delta \ln TFPQ$
	(1)	(2)	(3)	(4)
$\hat{\beta}_1$	-0.011*	0.005	-0.012**	0.004
	(0.005)	(0.011)	(0.006)	(0.012)
$\hat{\beta}_2$	-0.013	-0.003	-0.012	-0.018
	(0.009)	(0.016)	(0.008)	(0.017)
$\hat{\beta}_3$	-0.018	-0.051***	-0.018*	-0.074***
	(0.011)	(0.016)	(0.011)	(0.021)
$\hat{\beta}_4$	-0.042***	-0.087***	-0.039**	-0.103***
	(0.009)	(0.018)	(0.009)	(0.024)
$\hat{\beta}_5$	-0.027**	-0.069***	-0.023***	-0.074***
	(0.011)	(0.024)	(0.012)	(0.025)
$\hat{\beta}_6$	-0.020	-0.050***	-0.021*	-0.058***
	(0.012)	(0.018)	(0.011)	(0.021)
$\hat{\beta}_7$	-0.043***	-0.097***	-0.040*	-0.085***
	(0.012)	(0.018)	(0.009)	(0.011)

Notes: This table reports the estimates of the effect of the credit supply shock on alternative measures of the cumulative growth rate of TFPR and TFPQ estimated using model (5). All regressions include bank-level controls, firm-level controls, industry fixed effects, and region fixed effects. Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table A.6: Response of prices to negative credit supply shocks
Alternative measures of prices

	$\Delta \ln P_j$ ($\sigma = 2$)	$\Delta \ln P_j$ ($\sigma = 8$)	$\Delta \ln P_j^{Rev}$	$\Delta \ln P_j^{Main}$
	(1)	(2)	(3)	(4)
$\hat{\beta}_1$	-0.033***	-0.013*	-0.019*	-0.021**
	(0.011)	(0.008)	(0.010)	(0.009)
$\hat{\beta}_2$	0.010	0.004	0.004	-0.016
	(0.026)	(0.007)	(0.016)	(0.021)
$\hat{\beta}_3$	0.035	0.037***	0.053***	0.049**
	(0.025)	(0.014)	(0.017)	(0.023)
$\hat{\beta}_4$	0.051*	0.038***	0.049***	0.050**
	(0.027)	(0.014)	(0.015)	(0.023)
$\hat{\beta}_5$	0.086***	0.039**	0.043*	0.076***
	(0.031)	(0.018)	(0.021)	(0.025)
$\hat{\beta}_6$	0.077**	0.034	0.041	0.043
	(0.031)	(0.020)	(0.026)	(0.032)
$\hat{\beta}_7$	0.091***	0.020	0.044**	0.069***
	(0.034)	(0.018)	(0.017)	(0.016)

Notes: This table reports the estimates of the effect of a credit supply shock on alternative measures of the cumulative growth rate of prices estimated using model (5). All regressions include bank-level controls, firm-level controls, industry fixed effects, and region fixed effects. Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

confirm the overall findings of the paper.

Third, as an additional robustness check, we look at the change in the price of the main product of the firm (defined as the product with the highest revenue share), without taking a stance on aggregation across different products. The estimation results, reported in column 4 of Table A.6, are largely in line with the estimates obtained using the CUPI price index.

Inventory adjustment in response to the credit supply shock. Table A.7 shows the response of firm-level inventories to the credit supply shock. Column 1 shows that firms borrowing from legacy lenders with larger sovereign holdings did indeed reduce inventories in the immediate aftermath of sovereign shock, relative to less exposed firms. Column 2 shows that, as expected, this response is driven by those producers that entered the crisis with larger inventory holdings.

Table A.7: Response of inventories to negative credit supply shocks

	Short-term Δ(Inventories)	
	(1)	(2)
Shock	-0.029***	-0.014
	(0.010)	(0.010
Shock × Inventories		-0.091**
		(0.039)
R-squared	0.031	0.061
Observations	1024	1024

Notes: This table reports estimates of the effect of the credit supply shock on the change in inventories in the immediate aftermath of the shock (specifically, the growth rate of firm-level inventories of finished goods between 2009 and 2010). Column 1 reports the baseline effect estimated using model (5). In column 2 the baseline regression model is augmented to include an interaction between the shock variable the pre-shock stock of inventories. All regressions include bank-level controls, firm-level controls, industry fixed effects, and region fixed effects. Clustered standard errors are reported in parentheses. *** denotes significance at the 1% level, ** denotes significance at the 5% level, * denotes significance at the 10% level.

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